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Bingqing Song
City University of Hong Kong, bingqing.song@my.cityu.edu.hk

Yidi LIiu
The Chinese University of Hong Kong, Shenzhen, liuyidi@cuhk.edu.cn

Xin Li
The Hong Kong Polytechnic University, xin.li.phd@gmail.com

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RESEARCH ARTICLE

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Alike but Apart: Tie Decay in Social Commerce

Bingqing Song,[1] Yidi Liu,[2] Xin Li [3]
[1]Department of Information Systems, City University of Hong Kong, China, bingqing.song@my.cityu.edu.hk
[2]School of Management and Economics, The Chinese University of Hong Kong, Shenzhen, China, liuyidi@cuhk.edu.cn
[3]Department of Management and Marketing, The Hong Kong Polytechnic University, China, Xin.Li.PhD@gmail.com

Abstract

Ties between users play a fundamental role in the operation of social commerce, allowing product information to diffuse from sellers to (indirectly connected) customers. However, social commerce ties are mainly formed based on customers' interests in products, rendering them fragile. This study investigates the impacts of sellers' promotional activities on the decay of ties in social commerce. Drawing on utility theory, we posit an inverted U-shaped relationship between the alignment of sellers' promotions with customers' interests and tie strength due to customers' trade-off between surprise and fit in their consumption of product information. Moreover, we argue that the interest alignment effect is reinforced by multiple promotions (i.e., promotion count), flattening the nonlinearity of the inverted U-shaped impact and pushing the turning point to the right. We confirm these arguments via dyadic empirical analyses of a large Chinese social commerce website. The results inform social commerce practitioners of what is central to success and offer significant theoretical implications.

Keywords: Tie Decay, Social Commerce, Relationship Maintenance, Interest Alignment

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1 Introduction

Social commerce, an integration of social networking and e-commerce (Chen & Shen, 2015), has revolutionized the way sellers engage with customers through an innovative business model that allows retailers to connect with their target customers via social ties. As illustrated in Figure 1, social commerce sellers often showcase their products to followers, who may then engage by providing comments, likes, and shares. These user activities are further disseminated through the social network to each follower's friends and connections, resulting in the diffusion of product information (Cheng et al., 2011). With exposure to product information through the social network, some users (directly or indirectly connected with the seller) may become interested in the product and eventually make purchases. Many social networking companies have embraced this business model (Chen et al., 2016; Molina-Prados et al., 2022). For example, Meta allows users to create Facebook Shops within the Facebook platform. Instagram and Pinterest support the use of product tags and product pins to highlight shoppable products. Global retail sales in the social commerce market have been estimated to reach 2 trillion USD in 2025 (Bruijn et al., 2023).

Social commerce is distinct from traditional e-commerce, where customers typically search or receive recommendations to discover products (Li & Karahanna, 2015). Social commerce offers a social filtering mechanism that allows customers to "encounter" products they may like through their social ties (Chen et al., 2020). Since social ties not only facilitate the propagation of promotional information but also enhance the perceived authority and trustworthiness of received information (Arazy et al., 2010), sellers in social commerce can derive value from their networks. Due to the power-law distribution of followers, two distinct types of sellers exist in social commerce, each adopting different strategies. On the one hand, internet celebrities with a large number of followers (i.e., top influencers) can leverage their followers' trust to endorse products and capitalize on their large scale to offer significant discounts or exclusive items. On the other hand, the majority of small- and medium-sized sellers often rely heavily on social networks' cascaded propagation to reach a larger audience for more sales. For example, on Pinterest, a platform where users actively seek creative ideas, following and sharing are particularly effective in spreading posts on the platform. In this study, we are interested in supporting these smaller sellers in developing and maintaining social ties in their networks to disseminate promotional messages to directly and indirectly connected users (Dong & Wang, 2018; Wang et al., 2023).

Developing and maintaining social ties in social commerce involves two key processes: tie formation and tie decay (also termed tie dissolution, tie break, or tie persistence). Although both tie formation and tie decay are essential to social networks (Ahuja et al., 2012), existing research has primarily investigated customer development in social commerce (Zhang & Benyoucef, 2016), leaving tie decay as an underexplored yet critical phenomenon that we focus on in this study. In tie decay research, some literature uses the same factors from tie formation research (e.g., homophily) to explain tie decay (Burt, 2000). However, the mechanisms underlying tie decay are fundamentally different from those driving tie formation, as decay decisions depend on accumulated relationship experiences rather than initial connection potential. Specifically, tie decay is mainly influenced by the quality of the relationship and shared experiences (Dahlander & McFarland, 2013). Such information can only arise from a formed relationship and is unavailable prior to tie formation. Furthermore, the same factor may have different effects on tie decay and tie formation. For example, Deng et al. (2024) found that demographic homophily has a lower impact on tie dissolution than on tie formation.

Beyond the context of social commerce, tie decay is a common challenge in social networks (Burt, 2000). Friends may unfriend each other (Martin & Yeung, 2006); colleagues may cease collaboration (Jonczyk et al., 2016); partners may terminate relationships (Ding et al., 2023). Offline tie decay may be caused by changes in living contexts, personal conflicts, or natural disasters. For example, Bertogg and Koos (2022) showed that about one fourth of people in Germany lost contact with a friend during the pandemic. Online social networks are more robust to geographical restrictions, but they may be easily influenced since they lack concrete offline connections (John & Katz, 2023; Kivran-Swaine et al., 2011). However, the context of social commerce poses more challenges when investigating the tie decay problem. First, social commerce ties are commercial in nature and highly dependent on customers' interests in products. Indeed, sellers on the social commerce platform usually limit their posts to commercial content, as required by the social commerce platform. As in other commercial relationships, continually maintaining strong connections and effective engagement with customers is challenging (Kwak et al., 2011). Customers' interest in a seller could fade, causing tie decay. Second, a seller may have a substantial number of followers and indirectly connected customers, which makes it difficult to cater to their diverse interests and preferences to maximize engagement (Yin et al., 2023). Thus, to optimize sellers' online promotion activities, it is necessary to understand the factors that contribute to tie decay. Because people engage in social commerce for different underlying purposes (seeking product information rather than seeking social recognition), conclusions drawn from generic social networks may not apply to social commerce.

Figure 1. Cascaded Propagation of Product Information in Social Commerce

The tie decay problem is also related to relationship maintenance, a critical stage of customer relationship management (CRM) in marketing research. Tie decay and relationship maintenance share a common problem: keeping current customers (Aurier & N'goala, 2010). Like social commerce sellers, individuals and organizations employing CRM also utilize social media to enhance relationship management effectiveness (Trainor et al., 2014). However, classical CRM studies often focus on an organizational context (Payne & Frow, 2005; Reinartz et al., 2004), where the firms or brands invest in loyal customers who have higher profitability (Oliver, 1999) and make repeated purchases (Dick & Basu, 1994). These firms or brands usually utilize relationship marketing strategies like loyalty programs and direct mailings to retain customers (Gruen et al., 2000; Verhoef, 2003). This study focuses on individual social commerce sellers who serve customers through online social networking. Most of these sellers lack direct access to customer information and personalized interaction capabilities, causing more challenges in managing social ties. Thus, we are mainly interested in the promotion strategies of individual sellers who must target all potential customers through their direct followers. In this setting, tie decay in social commerce stands out as a practically important, theoretically challenging, and unresolved problem in literature.

To address this gap in the literature and offer practical managerial insights, we examine how promotional activities affect tie decay in social commerce. We focus on promotional activities since they constitute the major instrument of interest to both sellers and customers and play a unique role in social commerce. According to utility theory, customers' decisions to stay in a social commerce tie partially stem from the potential benefit of receiving new product information (Kleinbaum, 2018; Westphal et al., 2006). Based on this rationale, we inspect the extent to which a seller's promoted products are aligned with customers' interested products. We argue that customers expect to receive surprising yet relevant product information that aligns with their needs, which leads to an inverted U-shaped relationship between interest alignment and tie strength. We project that the effect of promotion content would be reinforced by the number of messages sent (i.e., promotion count within a period), which has a moderating effect.

To test these hypotheses, we conducted an empirical study using a dataset from a large social networking community in China. Following existing studies (Choi et al., 2018; Grover et al., 2002; Putzke et al., 2010), our study is at the dyadic level of seller-customer pairs. After addressing the endogeneity issues, we indeed found an inverted U-shaped relationship between the alignment of sellers' promoted products with customers' interested products and tie strength. Specifically, the increase of alignment initially strengthened ties but further increases reduced tie strength beyond an optimal point. We also found that the promotion count moderated the effect of interest alignment on tie strength, which made the inverted U shape of the interest alignment effect flatter. The findings were stable under various robustness checks. Furthermore, we differentiated between long-term ties signifying loyal customers and short-term ties likely arising from temporary promotions, and observed that the findings mainly apply to long-term ties, which are the core of social commerce networks.

This study has significant theoretical and practical implications. First, from a theoretical perspective, it enriches our understanding of tie decay in the context of social commerce. In particular, we found that high alignment between sellers' promoted products and customers' interested products did not necessarily strengthen ties. The findings also extend the CRM literature to the context of social commerce and individual sellers, highlighting the intermediary potential of social commerce sellers in facilitating firms' CRM capability. Second, we examined the interaction effect between interest alignment and promotion count. In particular, our study extends previous advertising studies on the annoying effect of ads (Goldstein et al., 2014; Todri et al., 2020), where overpromotion has adverse effects. Our framework provides new insights into this problem of overpromotion leading to reduced interest alignment, identifying promotion count as a secondary factor in reinforcing the inverted U-shaped relationship. Third, from a practical standpoint, the findings provide insights that can help social commerce sellers, particularly medium- and small-scale ones, to optimize the management of social ties through commercial activities. The findings also inform firms on how to optimize CRM. We conclude that to enhance customer engagement, sellers must consider the nuances in the balance of interest alignment and novelty. Social commerce platforms should therefore consider developing tools to help sellers assess their customers' interests in order to facilitate tie retention and improve product promotion recommendations (Arazy et al., 2010).

2 Theoretical Basis

2.1 Tie Decay in Social Commerce

Social ties contribute unique value to social commerce. For sellers, social ties constitute a crucial source of trust (Arazy et al., 2010). The trust accumulated in a social tie enhances customers' willingness to engage with, absorb, and act on sellers' information (Arazy et al., 2010; Levin & Cross, 2004). Previous studies have demonstrated that social ties can influence supply chain partnerships (Ding et al., 2023), customer demand (Karanam et al., 2023), decision-making quality (Zhang & Godes, 2018), recommendation acceptance (Arazy et al., 2010), IT adoption (Wu et al., 2017), and sales growth (Tuli et al., 2010). Therefore, weakening social ties (i.e., tie decay) profoundly threatens the success of social commerce.

Tie decay in social commerce, fundamentally grounded in preexisting social ties, as a distinct form of seller-customer relationship, is related to CRM in the marketing literature. The classical CRM literature emphasizes both economic incentives and social attributes in relationship management instruments (Berry, 1995). Given the evolution of online retail, CRM may also involve social media (Trainor et al., 2014). However, there is still a lack of research examining the implications of product promotions on relationship maintenance (Steinhoff et al., 2019), which is the foundation of social commerce.

Meanwhile, the social commerce context is different from traditional CRM settings. Unlike the traditional CRM context, where the subjects building relationships with customers are usually organizations, firms, or brands (Payne & Frow, 2005; Reinartz et al., 2004), social commerce sellers are usually individual sellers and, rather than acting as direct product providers, they serve an intermediary role between brands/firms/products and customers. This intermediary role constrains their competitive advantage to promotion strategies rather than product prices or quality. Unlike firms' online CRM efforts, social commerce sellers may only feed their target customers product information. This signifies the distinction between social commerce sellers and the typical organizations in CRM studies.

Due to the unique setting of social commerce, customers always expect to discover interesting products that fit their tastes through social ties, which helps reduce their search costs and cognitive load (He et al., 2019). Customers' utility may derive from various aspects of social ties, such as social value (Zhang & King, 2021) and material value (Dahlander & McFarland, 2013). But to manage ties, customers also incur costs, such as information processing loads, which lead to tie decay. Thus, based on utility theory, customers evaluate the trade-off between the benefits and costs of maintaining a tie (Kleinbaum, 2018; Westphal et al., 2006).

Existing literature on tie decay often focuses on generic social networks, such as friendships (Burt, 2000; Choi et al., 2018), which differ substantially from the commerce-based relationships in social commerce. Table 1 summarizes some research on tie decay in different contexts and with different focal points, with the majority of studies exploring real-world and social media friendships instead of social commerce relationships. For example, Martin and Yeung (2006) found that triadic relations impact the decay of real-world friendship ties. In the social media context, Burke and Kraut (2014) demonstrated that similar relationship maintenance activities on Facebook yielded different impacts on tie strength depending on the tie type (such as professional, relative, friend, romantic, or familiar stranger relationship).

In Table 1, we classify antecedents of tie decay into three groups: network (structure), individual (characteristics), and activity factors. Network factors refer to the network measures associated with a person or connection in the social network, such as homophily and embeddedness. Several studies have considered or controlled for network factors, such as the number of common ties (embeddedness) (Burt, 2000; Kivran-Swaine et al., 2011), similarity in age and gender (homophily) (Zhang & King, 2021), and mutual following relationships (reciprocity) (Jiang et al., 2019; Kwak et al., 2011). In social network studies, Aral and Walker (2014) argued that shared experiences and mutual friends are essential for fostering close relationships on Facebook. However, intricate network structures often prove difficult for individual users to directly manipulate.

Individual factors refer to individual characteristics, such as demographic characteristics. Jiang et al. (2019) found that a followee's characteristics (e.g., age) could cause followers to terminate the relationship. In supply chains, higher supplier gross margins and customer accounts payable have been found to mitigate the dissolution risk of supply chain relationships. In communities, marital and fertility status have been shown to influence tie persistence among group members (Martin & Yeung, 2006). In organizations, changes in positions within a hierarchy (Burt, 2000), such as a promotion (Jonczyk et al., 2016) or a change in the group (Kleinbaum, 2018), have also been found to affect tie decay. Such individual characteristics largely determine whether generic friendships persist. However, in social commerce, it is harder for people to observe each other's characteristics. Additionally, sellers find it difficult to influence customers by strategically manipulating their characteristics.

Table 1. Summary of Tie Decay Research

Study	Context	Tie between	Network factors	Individual factors	Activity factors	Methodology
(Burt, 2000)	Bankers	Colleagues	Embeddedness, homophily, and inertia	Social hierarchy		Empirical
(Jonczyk et al., 2016)	Company	Colleagues	Embeddedness, homophily, and redundancy	Trust, social hierarchy, and demographics		Behavioral
(Martin & Yeung, 2006)	Community	Real-world friendship	Embeddedness and homophily	Demographics and geolocation		Behavioral
(Ding et al., 2023)	Supply chain	Suppliers and buyers	Embeddedness	Supplier and buyer characteristics		Empirical
(Kleinbaum, 2018)	Students	Classmates	Embeddedness, homophily, and reciprocity	Personality		Empirical
(Kivran-Swaine et al., 2011)	Twitter	Twitter followers	Embeddedness and homophily	Prestige		Empirical
(Kwak et al., 2011)	Twitter	Twitter followers	Embeddedness, reciprocity, and duration		Content informativeness	Behavioral
(Burke & Kraut, 2014)	Facebook	FB friends	Homophily		Posting and communication frequency	Behavioral
(Ellison et al., 2014)	Facebook	FB friends	Embeddedness	Demographics	Posting and communication frequency	Behavioral
(Jiang et al., 2019)	GitHub	GitHub followers	Embeddedness and reciprocity	Demographics and language similarity	Activity frequency and project similarity	Behavioral
(Zhang & King, 2021)	Physicians	Colleagues	Embeddedness and homophily	Demographics and geolocation	Behavior similarity and informativeness	Empirical

Activity factors, defined as user actions on connected others, also influence the strength of ties. For example, on social media, activities like posting comments, giving likes, and sharing photos can help maintain social ties (Burke & Kraut, 2014; Ellison et al., 2014). As illustrated in Table 1, the frequency of activities is often examined in studies on Facebook (Burke & Kraut, 2014; Ellison et al., 2014) and GitHub (Jiang et al., 2019). Other studies have focused on the semantics of users' activities, which vary by context. For instance, Zhang and King (2021) studied professional relationships and found that differences in moral integrity, as reflected by individuals' activities, affected collaboration networks. This paper is the closest to our study, but our paper focuses on a social commerce context. Song et al. (2019) investigated how providers' content similarity in posting categories on YouTube affected their connections with each other and benefits from the video content. However, they only paid attention to the tie formation stage and did not account for ties to customers. Although tie formation is important, upon formation, tie decay/maintenance becomes the focus of sellers' CRM, as new customer acquisition costs in e-commerce are high[1] and repeat customers are usually more profitable (Oliver, 1999).

Our study focuses on a specific social commerce context where sellers can only attract customer purchases through the propagation of promotional information in social networks. Sellers cannot directly access customer information and do not have competitive advantages in product quality or pricing. Such sellers have more challenges in maintaining customer relationships that need to be addressed. They do not have non-commercial activities (such as content creation or live streaming) to maintain connections with customers, and can only share product information through the social commerce platform (Xiao et al., 2015). They also lack direct paths

[1] http://cen.ce.cn/more/202212/05/t20221205_38269067.shtml. Domestic new customer acquisition costs in e-commerce are between 54 and 82 USD, driving e-commerce platforms to foreign markets.

to communicate with target customers, such as the group chat functions in Facebook Marketplace and WeChat Business (Chang et al., 2020). Such group chat functions are derived from social media and leverage friendship relationships to build commercial ties (Yang et al., 2016), which is not the focus of our study.

The distinctive nature of social ties in the context of social commerce, combined with the lack of research investigating social tie decay phenomena in this area, constitutes a gap that needs to be filled. Based on the foundation of existing studies, we take the initiative to study tie decay in social commerce and focus on how sellers' promotional activities may affect tie decay.

2.2 Hypotheses Development

Consistent with prior research on seller-customer relationships (Choi et al., 2018; Grover et al., 2002; Putzke et al., 2010), this study takes a dyadic view to model social ties and conceptualizes tie decay in social commerce as a promotion-response process where sellers disseminate product information to customers and customers decide whether to keep the tie. Figure 2 illustrates our conceptual framework, which focuses on the effect of the relevance between sellers' posts (promotion content) and customers' interests and on how this effect may be reinforced by the promotion count (within a period). Other factors that may influence the process are included as control variables.

2.2.1 A Reasoning Framework

According to utility theory, customers' decisions are based on the trade-off between the benefit and the cost of maintaining a tie (Kleinbaum, 2018; Westphal et al., 2006). The cost is the cognitive load of digesting information from the tie. The benefit is the potential economic or entertainment value that customers receive from promotional information. Customers' trade-offs between these two aspects can be modeled as the following utility function:

$$U_t = \sum_{i=1}^{N_t} f(Alignment_i) + \beta N_t - \gamma N_t, \qquad (1)$$

where U_t is the user's perceived utility in time period t, which determines tie strength and tie decay. N_t is the number of promotional messages received in the time period t. $f(Alignment_i)$ defines the benefit received from each message as being relevant to the customer's interest. In addition to this per-message effect, we considered a common potential benefit per message β. We also assumed a common information processing cost per message γ. As shown in the equation, the user's overall utility (and later, tie decay) is determined by the sum of the value provided by relevant messages and the cognitive cost to process N_t messages.

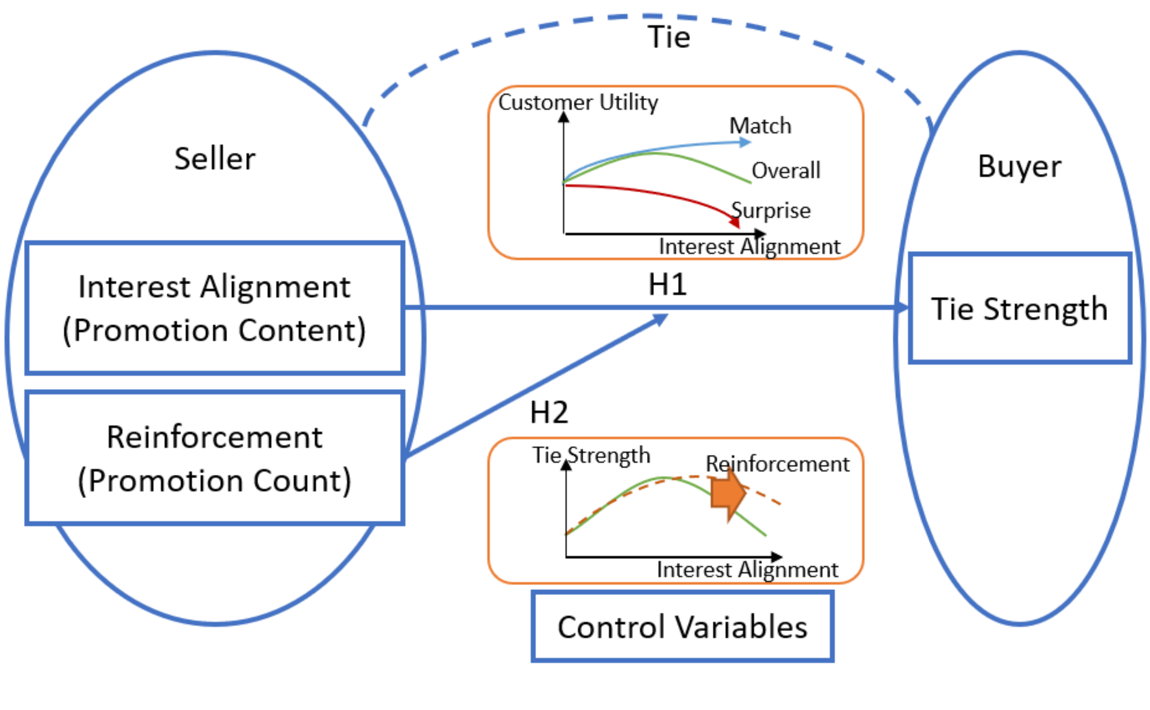

Figure 2. Conceptual Framework

Further, we transformed the sum of message relevance to the interaction of average relevance per message $f^*(AvgAlignment_t)$ and the number of messages N_t for our empirical study:

$$U_t \cong f^*(AvgAlignment_t) \times N_t + (\beta - \gamma) \times N_t \qquad (2)$$

Under this setup, the main effect of N_t depends on the overall value and cost per message, β - γ, which could be website-specific and is not studied in this paper. Our interest is in the interaction term, $f^*(AvgAlignment_t) \times N_t$, which depends on the nonlinear effect of interest alignment, $f^*(\,)$, and the reinforcement effect of N_t. Below, we detail our hypotheses.

2.2.2 Effect of Interest Alignment (Promotion Content)

Prior literature has emphasized the importance of seller-customer alignment (Li & Karahanna, 2015). We argue that the alignment between the seller's promotional messages and the customer's interests directly affects the perceived value of the social tie.

On the one hand, higher interest alignment would increase the customer's perceived value of the tie, leading to a higher likelihood of the customer keeping the tie. A strong product fit will enhance customer satisfaction and foster a favorable attitude toward the seller (Hong & Pavlou, 2014). In social commerce, when a seller consistently posts products that align with a customer's interests, following the focal seller's account significantly will reduce the customer's search costs (e.g., time and information load) (He et al., 2019) and increase the utility derived from maintaining the tie. Moreover, a customer is likely to develop an emotional attachment to a seller when the seller consistently delivers content that aligns with the customer's interests (Reagans, 2011).

On the other hand, making the promotion novel, up-to-date, and refreshing necessitates certain misalignment with the customer's existing or previous interests, which should add to the customer's utility of keeping the tie. In addition to product fit, customers generally value novelty and surprise (Hirschman, 1980), and will be satiated with repeated experience (Coombs & Avrunin, 1977). The optimal distinctiveness theory implies that people need both similarity and variety, which can be met in an optimally distinctive group (Brewer, 1991; Sun et al., 2019). In e-commerce, customers often demand diversity in product recommendations (Adomavicius & Kwon, 2014), while excessive similarity causes negative emotions (Snyder & Fromkin, 1980; Zeng & Wei, 2013). In practice, sellers may attempt to infer buyers' interest by observing buyers' past responses, which is a delayed measurement. Over time, a customer's real interest will drift from its historical trajectory (Ma et al., 2007). In this case, aligning closely with customers' historical interests may lead to suboptimal results by capturing customers' most recent (and unobservable) interest, which may cause annoyance and ignorance (Todri et al., 2020).

These two competing effects would make the overall effect of interest alignment on tie decay nonlinear. Specifically, we project that when the interest alignment level is low, the positive effect dominates, and the value of a tie is mainly reflected in fitting product purchases and reduced search costs. In contrast, when interest alignment is high, the negative effect will be stronger, as customers seek novelty and surprise. Overall, we hypothesize:

H1. The alignment between sellers' promotional messages and customers' recent interests has an inverted U-shaped effect on tie strength.

2.2.3 Effect of Reinforcement (Promotion Count)

In addition to interest alignment's direct effect on tie strength, we consider how this effect may be reinforced by promotion count. It should be noted that the prior condition for assessing promotion content is that a promotion must exist in the first place. If sellers do not have sufficient activities, they cannot be recognized by customers. A seller's engagement in approaching customers may imply diligence in doing the job (Christen et al., 2006) and signal quality (Erdem et al., 2008). In GitHub, Jiang et al. (2019) found that developers with fewer activities face a greater risk of being unfollowed. However, as discussed and illustrated in Equation (2), our main interest in this paper is the interaction between promotion count and interest alignment.

Similar to Hypothesis 1, we build our arguments based on how promotion count would affect the matching of customers' interests and the surprise of encountering new products. First, for the benefit of increased impressions of products aligning with customer interest, as illustrated in the left panel of Figure 3, more (frequent) product impressions reduce customers' search costs and increase customers' utility (Xu et al., 2011). With higher interest alignment, more promotion activities could present customers looking for fitting products with a steady and aligned stream of product information. The curve of the benefit from matching is then pushed up through the reinforcement of the promotion count. In addition, promotion content consistency might also strengthen a customer's trust in a seller's expertise (Peters et al., 1997): A consistent set of promotions serves as a credential of the seller's knowledge and expertise on a specific topic. If these consistent promotions are aligned with the customer's interests, they will increase their trust in the seller and the perceived utility of the tie.

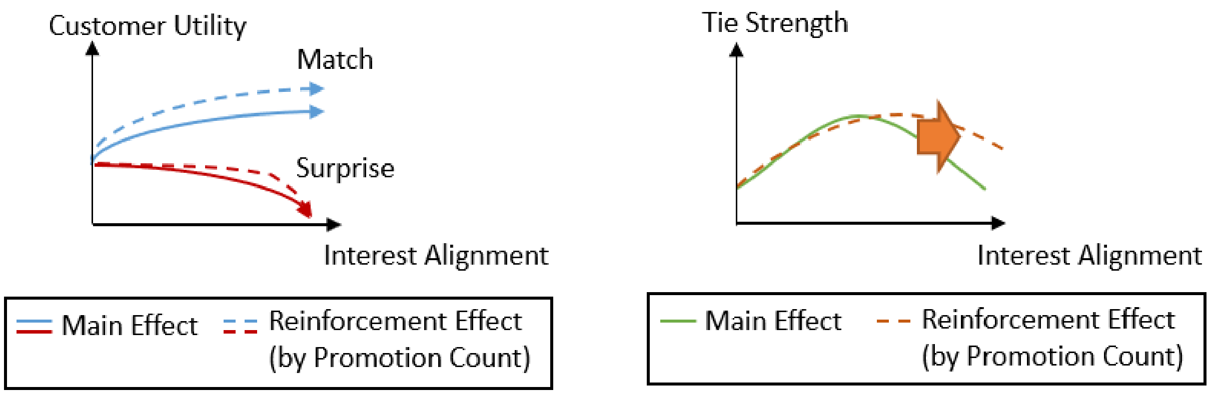

Figure 3. Promotion Count's Reinforcement Effect

Second, for customers seeking novelty, a high promotion count would also contribute to more impressions of novel products (as long as interest alignment is not 100%, where no novel product is provided). Consuming different items in this way has been found to combat satiation (Ratner et al., 1999). Even though more product promotions also result in processing costs and lead to more items with high similarity, prior research shows that consumer satiety is influenced by their perception of a variety of products consumed (Kahn & Wansink, 2004). Under a passive reading mode of social commerce, what surprises the customers are occasionally novel items, which lead to increased expectations of variety in the future (Sevilla & Redden, 2014). Thus, more promotions will push the customers' disutility curve of surprise up (to a smaller absolute value) as long as interest alignment is not 100% (left panel of Figure 3).

Overall, by considering these two mechanisms, we argue that the promotion count's reinforcement effect on tie strength will lie in the right panel of Figure 3, where the inverted U-shaped curve of interest alignment effect is pushed up (to be flatter), with the top of the curve extended to the right side. Specifically, we hypothesize:

H2a: Sellers' promotion count moderates the effect of interest alignment, pushing the inverted U shape of the interest alignment effect to be flatter.

H2b: Sellers' promotion count moderates the effect of interest alignment, pushing the top of the inverted U shape of this effect to the right.

3 Research Context

We conducted our study with data from Douban Dongxi. This social commerce site was built on Douban, one of the largest social networking communities in China focusing on online networking and social sharing. On Douban, some users shared exceptional or niche products they encountered, and Douban funneled this specific type of social sharing into a stand-alone website.[2] The Dongxi platform (active 2013-2017) was developed with the intention of letting users share products and guiding them to the shop URL for purchase on other e-commerce websites. Sellers on the Dongxi platform only posted product information and shopping hyperlinks and could not directly sell products to customers or access customer purchase information. Since the website focused on product sharing, Dongxi provided a unique context for our study. Due to the site's commercial nature, it was possible for sharers to post links with reference tags for a commission or share their own shop products. However, such activities would not have affected our study. The design of Dongxi largely limited non-commercial activities that were product irrelevant, providing us with a neat setup to isolate the impact of commercial activities.

As shown in Figure 4, sellers could place their product posts in a collection/list (called Doulie) to share details of their offerings, providing product information such as the product name, photos, purchasing channels, and a brief description. (It is possible that some users may have posted content that was irrelevant to the product; however, the website conducted regular checks to screen out such spam posts.) When browsing the product page, users could like or bookmark the product. Below the product information was the comment zone, where interested users could comment on the products and ask questions. Through these interactions, users were able to form following relationships or develop connections with each other.

[2] https://www.pingwest.com/a/34167 [*Dongxi: an online marketplace without spammers*] https://www.woshipm.com/operate/54660.html [*Can one make money on Dongxi?*]

Figure 4. A Product Page on Douban Dongxi

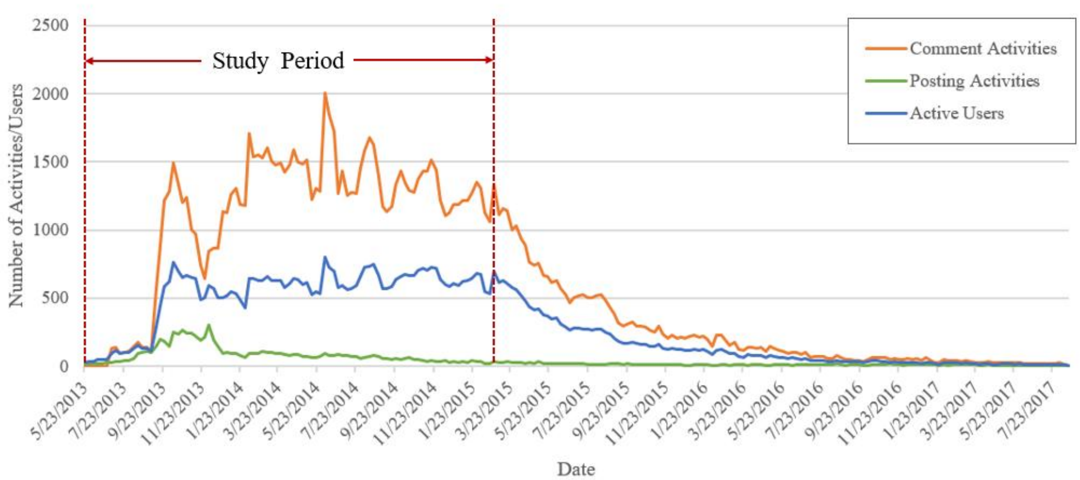

Figure 5. Active Users and Promotion/Comment Activities on Dongxi

Social ties and interpersonal following relationships on Dongxi supported users' product discovery. They affected the first-page recommendation, which is created based on users' following and browsing data. After following an account, users could also observe the product updates of their followees. When a user liked, commented on, or forwarded the promoted product, those activities were reflected on the product collection page and could then be viewed by connected friends, which diffused the promotional information to a larger audience across the user's social network on the platform.

The Dongxi site started operations in 2013 and ceased all activities by 2017. In this study, we collected all user activities from May 23, 2013, to August 17, 2017, covering the entire lifecycle of the platform. Specifically, our data captures 30,701 registered users, 400,997 individual posts, and 1,833,432 comments. Figure 5 shows the number of weekly active users with more than one action on the website, the number of posted products, and the number of comments on Dongxi over time. As we can see, before September 2013, the website was in the initialization stage without intensive activities. After that, it experienced a one-year active period, with consistently active users and customer comments. In 2015, the website moved into a decay stage with fewer and fewer user activities until its formal shutdown in September 2017. The decay and shutdown of the website provide us with a suitable testbed to inspect tie decay. We used data from May 23, 2013, to February 26, 2015 (before platform decay) to study the impact of sellers' promotional activities on tie decay.

4 Econometric Analysis

4.1 Tie Identification and Break

We first define social ties between sellers and customers. In this study, we used users' interactions rather than following relationships to identify social ties, avoiding the problem of "zombie" followers in social networks (Hou et al., 2021) and ensuring better validity (Putzke et al., 2010). Even if some users still follow a seller, ties between them may have already been broken. As discussed in previous research, users' active interaction is a more reliable measure of active relationships than explicitly reported friendship or follows (Kang et al., 2021; Wilson et al., 2009). Using explicitly reported following relationships to investigate tie decay might have caused biased results since that approach may capture only the most extreme cases (i.e., the user becomes so annoyed that they unfollow the seller) but miss the more common ones (i.e., the user ignores the seller and reduces interactions).

To distinguish sellers from customers on the platform, we followed the methods of Huang et al. (2022) and Chen et al. (2016) in defining a seller as a user who posts products for promotion and a customer as a user who comments on the seller's posted products. It should be noted that these roles are not mutually exclusive—individuals may alternatively assume seller or customer identities contingent on their exhibited behaviors on the platform at any given time. For instance, a user will play the role of a seller when posting products and the role of a customer when commenting on other users' posts. Since sellers can also reply to the comments under their posts, we followed the literature (Onnela et al., 2007; Putzke et al., 2010) in identifying social ties using the reciprocal communication of comments and replies. We consider a tie formed when there are two instances of reciprocal communication between two users. Thus, the seller initiates the formation of a tie, but the customer may break the tie by not responding to the seller's post (Kleinbaum, 2018). When a customer's responses to a seller stop for a certain time period (i.e., three months in this study), their tie can be considered broken. We tested thresholds other than the three-month threshold in our robustness check.

4.2 Model Specification

Having defined tie formation and break, we created a dynamic network by adding and removing links. We compiled week-level panel data for each tie to study tie decay. Since we considered the customer's decisions on whether to keep the tie in our analysis, we used the number of comments from the customer on the seller's product posts as a measure of tie strength ($TieStrength_{i,t}$) and used it as the dependent variable (Kim et al., 2018; Kim & Koh, 2023; Wu, 2013). A decrease in $TieStrength_{i,t}$ indicates tie decay. We built a fixed-effect model for tie i in week t as:

$$TieStrenth_{i,t} = \alpha + \beta_0 \times TieStrength_{i,t-1} + X_{i,t-1}\Gamma + X_{i,t-1}M_{i,t-1}\Psi + Control_{i,t-1}\Phi + \eta_i + \theta_t + \varepsilon_{i,t}, \quad (3)$$

where $TieStrength_{i,t}$ denotes the strength of tie i in week t. $TieStrength_{i,t-1}$ captures serial correlation. $X_{i,t-1}$ are the independent variables, $Interest\_Alignment_{i,t-1}$ and $Interest\_Alignment_{i,t-1}^2$, which capture the nonlinear effect of interest alignment on tie strength. $M_{i,t-1}$ is the moderating variable on promotion count, $Prod\_Num\_Seller_{i,t-1}$. $Control_{i,t-1}$ are the control variables, which are elaborated below. To address concerns about reverse causality, the dependent variable ($TieStrength_{i,t}$) was calculated during time period t, and all of the other variables, including independent variables, the moderating variable, and control variables, were calculated in time period t-1. We controlled for tie-fixed effects η_i and time-fixed effects θ_t to account for time-invariant heterogeneity for user pairs and market-level time-variant effects. $\varepsilon_{i,t}$ is the error term.

In the model, we log-transformed ($LN(X+1)$) the count variables and $Interest\_Alignment_{i,t-1}$ to address the skewed distribution. We also calculated the standard errors clustered at the tie level that are robust to potential heteroskedasticity and intragroup correlation.

4.3 Measurements

The independent variable $Interest\_Alignment_{i,t-1}$ reflects the degree of interest alignment between the seller and the customer in tie i. We calculated this measure based on the similarity between the products the seller promotes and the products the customer is interested in. Here, we proxied customers' interest by the commenting behavior on the promoted products, where we considered customers to have a higher interest in the products they commented on more (Baker et al., 2011; Vessey & Ward, 2013).

We employed textual similarity between the titles and the descriptions of seller-promoted products and those of customer-commented products as our measure of interest alignment. Since there were multiple products posted by sellers and commented on by customers each week, we concatenated all the titles and descriptions of the multiple products as one piece of text. Then, we converted the product title and the description text into a term frequency representation. As the data was in Chinese, we conducted word segmentation using the *jieba* package in Python. The Chinese words and the frequency with which they appear in the text (concatenated from multiple products) form a vector. Then, we applied cosine similarity on this term frequency vector to construct the similarity measure following Burtch et al. (2022) and Dyer et al. (2024) as follows:

$$Interest\_Alignment_{i,t-1} = \begin{cases} \frac{Seller\_txt_{i,t-1} \times Customer\_txt_{i,t-1}}{\|Seller\_txt_{i,t-1}\| \times \|Customer\_txt_{i,t-1}\|}, \\ if\ \|Seller\_txt_{i,t-1}\| > 0\ and\ \|Customer\_txt_{i,t-1}\| > 0, \\ 0,\ otherwise \end{cases} \tag{4}$$

where $Seller\_txt_{i,t-1}$ and $Customer\_txt_{i,t-1}$ are the term frequency vectors of text concatenated from the product titles and descriptions posted by the seller or commented on by the customer in tie *i* during week *t*-1.

The variable $Prod\_Num\_Seller_{i,t-1}$ is the number of products posted by the seller in tie *i* during week *t*-1, reflecting the promotion count. Note that $Prod\_Num\_Seller_{i,t-1}$ had a missing value when the seller did not post any product in week *t*-1, so only sellers with promotion posts were included in our dataset.

We incorporated multiple types of control variables to alleviate the omitted variable issue. One concern was whether the customers' reduced interest was toward a tie or the entire website. We controlled for customers' overall activities on the website to address this concern. We incorporated the number of ties involved ($Tie\_Num\_Customer_{i,t-1}$), the number of comments ($Com\_Num\_Customer_{i,t-1}$), and the sentiment of comments ($Com\_Sent\_Customer_{i,t-1}$) (details of the sentiment measure are elaborated in Appendix A1) in the model. We also controlled for the posting characteristics of the customer (in a seller role in relation to other users), including the number of products ($Prod\_Num\_Customer_{i,t-1}$) and the sentiment of the posted products ($Prod\_Sent\_Customer_{i,t-1}$).

In addition to promotion content, sellers' sentiment in interactions with customers could also affect tie decay. Thus, we controlled for the sentiment of the seller's replies sent to the customer in tie *i* ($Reply\_Sent_{i,t-1}$), which may have affected the customer's perception of the tie.

We also controlled for the seller's overall level of activities on the website, including the number of ties with other users ($Tie\_Num\_Seller_{i,t-1}$), the number of replies ($Reply\_Num\_Seller_{i,t-1}$), the sentiment of replies to other users ($Reply\_Sent\_Seller_{i,t-1}$), and the sentiment of product descriptions ($Prod\_Sent\_Seller_{i,t-1}$), which may have affected customers' perceptions.

Another concern arose from the interest alignment measure, which depends not only on the commonality between customers and sellers but also on the diversity of customers' or sellers' interests. For example, a customer group with a narrow range of interests may have different commonalities with the seller than a customer group with more diverse interests. Thus, we controlled for the diversity of products commented on by the customer in tie *i* ($Diversity\_Customer_{i,t-1}$) and products posted by the seller in tie *i* ($Diversity\_Seller_{i,t-1}$). The diversity of a user is the cosine similarity of text vectors between their posted/commented products (details are elaborated in Appendix A1).

Another concern was the uniqueness of one seller's products from other sellers' products. If multiple sellers are promoting a similar product, they may compete with each other. To address this concern, we controlled for the uniqueness of products posted by the seller in tie *i* compared with other sellers maintaining the ties with the customer in tie *i* ($Uniqueness_{i,t-1}$). The uniqueness was measured by the cosine similarity of text vectors between the focal seller's products and other sellers' aggregated products.

We also controlled for network factors. For example, customers may adjust their interactions with the seller based on their peers' behavior (Ma et al., 2015). To account for this network effect, we controlled for common friends between sellers and customers, as these common friends could enable peers to influence each other through observation (Kleinbaum, 2018; Zhang & King, 2021). Since the seller-customer pair is a directional relationship, we followed Song et al. (2019) to define four types of common friends according to the directions of commenting relationships. To control for these types of common friends in the model (as detailed in Appendix A1), we defined them as $Common\_Friends\_A_{i,t-1}$ to $Common\_Friends\_D_{i,t-1}$.

We further controlled for product price, as this may influence customers' behavior with regard to tie maintenance. For example, cheaper products tend to attract more attention from customers on the social commerce platform. So, we used the average price of the seller's products in tie *i* at week *t*-1 ($Avg\_Price_{i,t-1}$) as the control variable.

The evolution of the tie may suffer from a lifecycle where the connection between customer and seller becomes stronger first and then declines over time. Therefore, we controlled for tie age ($Tie\_Age_{i,t-1}$), which is the number of consecutive weeks since tie *i* was formed.

4.4 Endogeneity

In addition to the omitted variables, there could be unobserved variables correlated with customers' decisions on adjusting tie strength and sellers' promotion actions. For example, whether sellers and customers know each other offline may affect their common interests and ties in an online network. Following Tafti et al. (2022), we thus adopted the instrumental variable (IV) method to strengthen the identification.

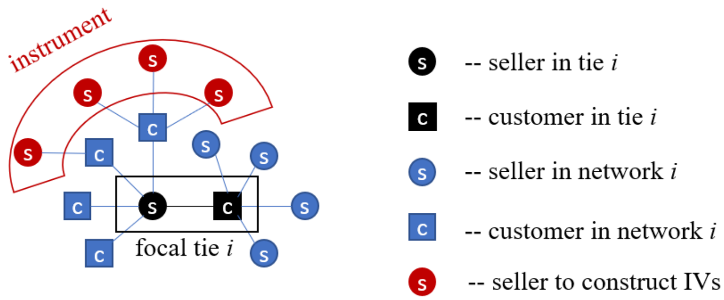

Figure 6. Illustration of Instrumental Variables

Table 2. Descriptive Statistics

Variable	Obs.	Mean	*SD*	Min	Max
$TieStrength_{i,t}$	29,878	0.035	0.366	0	23
$Interest\_Alignment_{i,t}$	29,878	0.159	0.134	0	1
$Prod\_Num\_Seller_{i,t}$	29,878	7.556	12.906	1	209
$Common\_Friends\_A_{i,t}$	29,878	1.002	2.762	0	41
$Common\_Friends\_B_{i,t}$	29,878	0.707	1.675	0	26
$Common\_Friends\_C_{i,t}$	29,878	0.447	1.519	0	27
$Common\_Friends\_D_{i,t}$	29,878	0.707	2.542	0	51
$Diversity\_Seller_{i,t}$	29,878	0.127	0.157	0	0.567
$Diversity\_Customer_{i,t}$	29,878	0.219	0.241	0	0.743
$Reply\_Sent_{i,t}$	29,878	0.007	0.115	-2.333	7
$Prod\_Sent\_Seller_{i,t}$	29,878	0.198	0.245	-3	7
$Reply\_Num\_Seller_{i,t}$	29,878	30.825	57.566	0	424
$Reply\_Sent\_Seller_{i,t}$	29,878	0.095	0.233	-4.500	7
$Tie\_Num\_Seller_{i,t}$	29,878	46.481	59.277	1	228
$Prod\_Num\_Customer_{i,t}$	29,878	3.389	11.128	0	209
$Prod\_Sent\_Customer_{i,t}$	29,878	0.068	0.180	-3	5
$Com\_Num\_Customer_{i,t}$	29,878	3.353	15.754	0	293
$Com\_Sent\_Customer_{i,t}$	29,878	0.046	0.261	-5	7
$Tie\_Num\_Customer_{i,t}$	29,878	24.757	65.198	1	532
$Tie\_Age_{i,t}$	29,878	9.147	11.798	0	82
$Avg\_Price_{i,t}$	29,878	118.502	4,851.566	0	265,000
$Uniqueness_{i,t}$	29,878	0.027	0.062	0	0.770

We included two network-based instrumental variables as illustrated in Figure 6: $Interest\_Alignment\_Others_{i,t-1}$, and $Prod\_Num\_Others_{i,t-1}$ for each seller-customer pair *i* in week *t*-1. These IVs are the average interest alignment and promotion count of other sellers that connect with customers in the seller's network in tie *i* at week *t*-1. Specifically, we first identified customers having ties with the focal seller in tie *i* and eliminated the focal customer in tie *i*. We called these customers friend customers in tie *i*. Friend customers further had ties with a set of other sellers (excluding the focal seller). These other sellers' average promotion count and interest alignment (between these sellers and their corresponding tied customers) were constructed as instrumental variables. In other words, the seller in tie *i* and the sellers in the two measures were both connected by the friend customer in network *i* and may have observed each other's behavior through the customer's posts and comments. Being influenced by peers, sellers may have changed their posting strategies. Thus, the two instrumental variables could have affected seller behaviors (relevance condition). However, since tie strength was determined by the focal customer, it was not likely to be influenced by these IVs (exclusion condition). Thus, these two variables should form valid instrumental variables.

5 Results

5.1 Summary Statistics

The dataset contains 4,900 social ties, involving 1,557 sellers and 2,353 customers from May 23, 2013, to February 26, 2015, leading to 29,878 week-level observations, as reported in Table 2. Note that fewer than 10% of users formed a tie with sellers. As shown, $TieStrength_{i,t}$ has a mean of 0.035, indicating that one average customer made 0.035 comments per week to a particular seller after the formation of their tie. The average $Interest\_Alignment_{i,t}$ is 0.159, implying a generally low level of interest alignment between the seller and customer. On average, a seller posted 7.556 products for promotion each week. The correlation between these variables is shown in Appendix Table A1.

5.2 Main Model Results

We report the main results in Table 3. Columns 1-2 are the fixed-effect model. Columns 3-4 are the two-stage least squares (2SLS) models with instrumental variables. The first-stage results of the 2SLS models are provided in Appendix Table A3, where we separately regressed endogenous variables, $Interest\_Alignment_{i,t-1}$, and $Prod\_Num\_Seller_{i,t-1}$, on all control variables and instrumental variables ($Interest\_Alignment\_Others_{i,t-1}$ and $Prod\_Num\_Others_{i,t-1}$). The Sanderson-Windmeijer F-statistics of the first-stage regressions (Sanderson & Windmeijer, 2016) are 466.97 for $Interest\_Alignment_{i,t-1}$, 372.96 for $Interest\_Alignment_{i,t-1}^2$, and 466.34 for $Prod\_Num\_Seller_{i,t-1}$ in Model 3 (179.67, 119.28, and 122.62 respectively in Model 4), which are higher than the critical value of 10.83 for a single endogenous regressor (Stock & Yogo, 2005) and indicate that the instrumental variables satisfy the relevance condition (Bascle, 2008). We calculated the Anderson canonical correlation LM statistics for the under-identification test and found that our results significantly passed the test. We calculated the Cragg-Donald Wald F-statistics for the weak identification test. The results for the 2SLS models were all higher than the 5% maximal IV relative bias (12.20) suggested by Stock and Yogo (2005). We also calculated the Hansen J statistics for the over-identification test; the results passed the test at the 5% significance level. Overall, our instrumental variables were valid for this analysis.

The OLS results and 2SLS results were generally consistent, except that the 2SLS results generally had a larger scale, showing that OLS underestimated the effects of the independent variable due to unobservable confounding factors, such as the other social interactions between sellers and customers (on Douban) that may have led to their common interests. Overall, Column 3 shows that the significantly negative coefficient on $Interest\_Alignment_{i,t-1}^2$ (β = -1.797, p < 0.01) and the significantly positive coefficient on $Interest\_Alignment_{i,t-1}$ (β = 0. 385, p < 0.05) imply an inverted U-shaped relationship between interest alignment and the tie strength, which supports Hypothesis 1. The U-shaped curve reaches the turning point when interest alignment is 0.113 ($e^{-0.385/(2\times-1.797)}-1$). When interest alignment is low, sellers' efforts to align product postings with customers' interests benefit the social tie by serving customers' preferences. Once the seller reaches a certain level of alignment with their customers, continued similarity may bore customers because of the reduced novelty and surprise.

Table 3. Regression Results of the Main Model

	(1)	(2)	(3)	(4)
DV: $TieStrength_{i,t}$	**OLS**	**OLS**	**2SLS**	**2SLS**
Direct effects				
$Interest\_Alignment_{i,t-1}$	0.138^{**} (0.067)	0.326^{***} (0.087)	0.385^{**} (0.173)	0.659^{*} (0.374)
$Interest\_Alignment_{i,t-1}^2$	-1.139^{***} (0.157)	-2.098^{***} (0.213)	-1.797^{***} (0.488)	-3.531^{***} (1.132)
$Prod\_Num\_Seller_{i,t-1}$	0.006^{***} (0.001)	0.003 (0.003)	0.013^{**} (0.005)	0.001 (0.012)
Interaction effects				
$Interest\_Alignment_{i,t-1} \times Prod\_Num\_Seller_{i,t-1}$		-0.117^{***} (0.034)		-0.223 (0.213)
$Interest\_Alignment_{i,t-1}^2 \times Prod\_Num\_Seller_{i,t-1}$		0.570^{***} (0.085)		1.168^{*} (0.623)
Constant	0.061^{***} (0.014)	0.065^{***} (0.015)		
Control variables	Y	Y	Y	Y
# of ties	3,562	3,562	3,292	3,292
# of observations	27,083	27,083	24,353	24,353
R^2	0.158	0.162	0.011	0.009
F-statistic	13.967	18.031	3.762	3.830
Underidentification test			$1,675.113^{***}$	630.028^{***}
Weak identification test			415.746	212.374
Overidentification test			7.564^{*}	8.307

Note: Standard errors in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01, control variable coefficients omitted and detailed in Appendix Table A2, time- and tie-fixed effects included across all models.

In Column 4, the interaction term of $Interest\_Alignment_{i,t-1}^2$ and $Prod\_Num\_Seller_{i,t-1}$ is significantly positive ($\beta = 1.168$, $p < 0.1$), but the interaction term of $Interest\_Alignment_{i,t-1}$ and $Prod\_Num\_Seller_{i,t-1}$ is insignificant. According to this specification, the inverted U-shaped curve will be flatter, and the turning point will increase along with the increase of $Prod\_Num\_Seller_{i,t-1}$ (as long as the log value of $Prod\_Num\_Seller_{i,t-1}$ is less than 3.023 (= 3.531/1.168)). To further illustrate the effect, we visualized the relationship of interest alignment, promotion count, and tie strength in Figure 7. In the figure, we set interest alignment between 0 and 0.3 (one standard deviation above the mean), and the log value of $Prod\_Num\_Seller_{i,t-1}$ is between 0 and 2.5 (actual post values range from 1 to 11). As we can see, when the promotion count is low, the effect of interest alignment shows an inverse U-shaped curve, which is what we expected. To strengthen a tie, sellers will need to run promotions that are not too close to (and not too far away from) their customers' interests. As the promotion count increases, sellers can run promotions to be more aligned with customers' interests. The optimal level of promotional activities, considering both interest alignment and product count, is depicted by the brown curve in Figure 7. Thus, Hypothesis 2 is supported.

It should be noted that our model (Figure 7) also explains the annoying effect of advertisements, as demonstrated in the marketing literature (Goldstein et al., 2014; Todri et al., 2020). If a seller repeatedly sends the same or a similar advertisement to a customer, the customer will get bored, and interest alignment will decrease. In this case, more advertisements would be suboptimal or could even be associated with a negative response (tie decay).

5.3 Robustness Check

We conducted several robustness checks to validate the findings. First, we changed the time window for the tie definition and the threshold for the tie break. In the main model, we did not constrain the time interval of reciprocal interaction. In the robustness check, we set a window size of 26 weeks (i.e., six months) and 52 weeks (i.e., one year) for tie definition, where only reciprocal interactions accomplished within 26 or 52 weeks were considered valid to form a tie. Table 4, Columns 1-2 report the results, which are consistent with the main results.

Second, we varied the thresholds for tie breaks. In the main model, we set the threshold of tie break at 13 weeks (i.e., three months). That is, ties between sellers and customers remain intact until 13 weeks after their last interaction. In the robustness check, we changed the threshold to 17 weeks (i.e., four months) and 26 weeks (i.e., six months), respectively. The results are reported in Columns 3-4 of Table 4 and remain robust with our findings in the main model.

Third, we controlled for a dummy variable that indicates whether the interest alignment is zero. When calculating the independent variable $Interest\_Alignment_{i,t-1}$, we used zero to fill out the missing value resulting from no posting or commenting activities on one side of the tie. Column 5 in Table 4 shows results that are consistent with the main model.

Fourth, in each tie, we controlled for the average product price and the uniqueness of the seller. Column 6 in Table 4 shows results that are consistent with the main model.

Fifth, we changed the analysis to a monthly level. Column 7 in Table 4 shows the results, which are consistent with our main model.

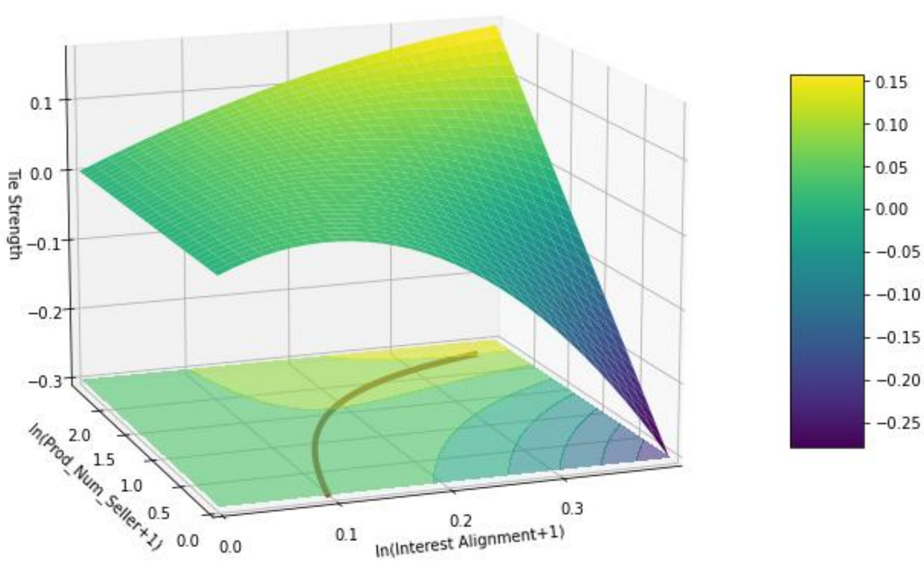

Figure 7. Nonlinear Effect of Interest Alignment and Promotion Count

Table 4. Robustness Check Results of Endogeneity Issues and Tie Identification

DV: $TieStrength_{i,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tie definition window	**26 weeks**	**52 weeks**					
Tie break threshold			**17 weeks**	**26 weeks**			
Analysis period							**Monthly**
Model	**2SLS**	**2SLS**	**2SLS**	**2SLS**	**2SLS**	**2SLS**	**2SLS**
Direct effects							
$Interest\_Alignment_{i,t-1}$	0.514 (0.322)	0.639* (0.378)	0.524** (0.212)	0.514 (0.322)	0.709* (0.386)	0.668* (0.376)	19.886** (9.486)
$Interest\_Alignment_{i,t-1}^2$	-3.112*** (1.007)	-3.444*** (1.147)	-2.528*** (0.767)	-3.444*** (1.147)	-3.632*** (1.152)	-3.534*** (1.134)	-63.442** (27.593)
$Prod\_Num\_Seller_{i,t-1}$	-0.002 (0.010)	0.002 (0.012)	0.001 (0.006)	-0.002 (0.010)	0.002 (0.012)	0.001 (0.013)	0.313** (0.124)
Moderating effects							
$Interest\_Alignment_{i,t-1} \times Prod\_Num\_Seller_{i,t-1}$	-0.172 (0.181)	-0.212 (0.215)	-0.192 (0.130)	-0.172 (0.181)	-0.231 (0.214)	-0.236 (0.214)	-11.090** (4.810)
$Interest\_Alignment_{i,t-1}^2 \times Prod\_Num\_Seller_{i,t-1}$	1.009* (0.547)	1.116* (0.629)	1.041** (0.441)	1.009* (0.547)	1.185* (0.625)	1.174* (0.625)	43.629** (17.044)
$Interest\_Dummy_{i,t-1}$					-0.019** (0.009)		
$Avg\_Price_{i,t-1}$						0.000 (0.001)	
$Uniqueness_{i,t-1}$						0.033 (0.027)	
Control variables	Y	Y	Y	Y	Y	Y	Y
# of ties	3,016	3,158	3,549	3,797	3,292	3,292	1,906
# of observations	22,269	23,410	29,959	39,757	24,353	24,353	5,151
R^2	0.011	0.011	0.006	0.010	0.009	0.010	-1.438
F-Statistic	3.733	3.850	3.704	4.069	3.709	3.644	2.806
RMSE	0.119	0.122	0.111	0.097	0.122	0.122	0.344

Note: Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, control variable coefficients omitted, time- and tie-fixed effects included across all models.

We also experimented with different measures of interest alignment. First, we represented products by product categories, following Zeng and Wei (2013) and Song et al. (2019), which can remove the influence of textual wording. We categorized products into four types: technology, life, fashion, and hobby, and presented the seller-published and customer-interested products with a vector:

$$Product_{i,t-1} = [Category_{i,t-1}^1, Category_{i,t-1}^2, Category_{i,t-1}^3, Category_{i,t-1}^4], \quad (5)$$

where $Category_{i,t-1}^k$ is the percent of seller-shared products (or customer-commented products) in each category. Then, we applied cosine similarity on the product category vector to their similarity. As another choice, we represented product text with text embedding using sentence-BERT (Reimers et al., 2019), which is more powerful in capturing the semantics of text. We used the *sentence_transformers* package and the *sbert-base-Chinese-nli* model (Zhao et al., 2019, 2023) in Python to get the embedding for the concatenated text of each seller or customer's interested products. Then, we calculated cosine similarity between vectors to measure interest alignment. The panel data results of the two measures are shown in Columns 1-2 of Table 5 and are consistent with our main model.[3]

We tested other estimators to strengthen the identification. First, following Qi and Han (2020) and Tafti et al. (2022), we used the generalized method of moments (GMM) estimation with the lagged dependent variable ($TieStrength_{i,t-1}$) as the control variable and used lagged endogenous variables ($Interest\_Alignment_{i,t-1}$ and $Prod\_Num\_Seller_{i,t-1}$) and instrumental variables ($Interest\_Alignment\_Others_{i,t-1}$ and $Prod\_Num\_Others_{i,t-1}$) in Section 4.4 as instruments in the GMM estimation. The results for GMM in Column 3 of Table 5 support our findings.

[3] We were not able to find valid instrumental variables for the two new measures. However, the panel data results still validate our findings.

Table 5. Robustness Check of New Measures and Estimators

	(1)	(2)	(3)	(4)
IDV measure	**Product category**	**Sentence-BERT**		
	OLS	**OLS**	**GMM**	**Heckman**
Direct effects				
$Interest\_Alignment_{i,t-1}$	0.068* (0.036)	0.031 (0.027)	0.658* (0.364)	0.655* (0.374)
$Interest\_Alignment_{i,t-1}^2$	-0.180*** (0.057)	-0.110*** (0.038)	-1.580*** (0.217)	-3.517*** (1.138)
$Prod\_Num\_Seller_{i,t-1}$	0.001 (0.002)	0.002 (0.002)	0.006 (0.012)	0.001 (0.012)
Moderating effects				
$Interest\_Alignment_{i,t-1} \times Prod\_Num\_Seller_{i,t-1}$	-0.049** (0.019)	-0.015 (0.014)	-0.211 (0.207)	-0.221 (0.213)
$Interest\_Alignment_{i,t-1}^2 \times Prod\_Num\_Seller_{i,t-1}$	0.110*** (0.030)	0.048** (0.019)	1.001* (0.604)	1.160* (0.627)
$IMR_{i,t-1}$				0.001 (0.024)
Control variables	Y	Y	Y	Y
# of ties	3,562	3,562	3,292	3,292
# of observations	27,083	27,083	24,353	24,353
R^2	0.156	0.155	0.013	0.009
F-statistic	9.641	9.214	3.651	3.682
RMSE	0.130	0.130	0.122	0.122

Note: Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, control variable coefficients omitted, time- and tie-fixed effects included across all models.

Additionally, we used the Heckman model to correct for sample selection bias. Our sample in the main model was restricted to the sellers who promoted at least one product in one week, so sellers who did not post products during that particular week were not included in the sample. To address the concern regarding such sample selection bias, we adopted a Heckman-type approach (Heckman, 1979). We estimated the selection process using the probit model with a dependent variable indicating whether the seller posted a product, and we regressed it on the explanatory variable $Prod\_Num\_Others_{i,t-1}$, and all control variables. Then, we generated the inverse Mills ratio (IMR) with the estimation result of the probit model. We further estimated the 2SLS regression by including the IMR as an additional control variable. The results in Column 4 of Table 5 support our findings.

5.4 Generalizability

The setting of our study, the Douban Dongxi platform, operated between 2013 and 2017, which may cause concern about whether the findings can generalize to the current social commerce context. We note that even though the platform was eventually phased out, it was successful in the first few years of its operation. In the main model, we studied the ties formed between May 23, 2013, and February 26, 2015, during which the website was in normal operation. To alleviate the concern about the generalizability of our findings, we varied the study period to be both longer and shorter. Columns 1-3 of Table 6 show the results for varied study periods and also for varied tie identification periods, which are all consistent with the main model.

We also explored other websites still in operation with a social commerce feature. In particular, we collected data from SMZDM.com, a product-sharing website powered by JD.com, which provides a social community for users to recommend products (such as discounts) on JD.com. SMZDM had 29 million registered users and 39 million average monthly active users as of 2023 (ZDM Co., 2024). Due to the large number of users on the platform, we used the snowball sampling method to collect records of 2,893 users with 212,286 products, 260,475 comments, and 97,380 replies that appeared on the product promotion channel (Jingxuan channel) between February 28, 2024, and September 15, 2024. The summary statistics are reported in Table A4 in the appendix. We conducted the same analysis as in the main model with the SMZDM dataset and found consistent results.

5.5 Long-Term vs. Short-Term Ties

We differentiated social ties into two categories, long-term and short-term ties, to inspect the heterogeneity of the impact of sellers' promotional activities. We considered long-term ties as a proxy for customer loyalty since loyal customers typically make repeated purchases and are thus the major target of relationship maintenance (Dick & Basu, 1994), offering lower maintenance costs (Fornell & Wernerfelt, 1987) and higher profitability (Oliver, 1999).

Table 6. Robustness Check Results of Sample Period and New Dataset

DV: *TieStrength$_{i,t}$*	(1)	(2)	(3)	(4)
Tie definition period	**5/23/2013 ~ 2/26/2015**	**5/23/2013 ~ 8/17/2017**	**5/23/2013 ~ 2/26/2015**	
Study period	**5/23/2013~ 8/17/2017**	**5/23/2013~ 8/17/2017**	**5/23/2013~ 5/22/2014**	
Website				SMZDM
Direct effects				
Interest_Alignment$_{i,t-1}$	0.560 (0.359)	0.570 (0.360)	0.744*** (0.263)	14.568*** (4.179)
Interest_Alignment$_{i,t-1}^2$	-3.156*** (1.082)	-3.142*** (1.077)	-3.781*** (0.928)	-31.264*** (8.426)
Prod_Num_Seller$_{i,t-1}$	0.003 (0.012)	0.005 (0.013)	0.000 (0.009)	0.024 (0.035)
Interaction effects				
Interest_Alignment$_{i,t-1}$ × *Prod_Num_Seller$_{i,t-1}$*	-0.206 (0.208)	-0.210 (0.209)	-0.195 (0.162)	-3.519*** (1.010)
Interest_Alignment$_{i,t-1}^2$ × *Prod_Num_Seller$_{i,t-1}$*	1.076* (0.608)	1.067* (0.607)	1.148** (0.524)	7.434*** (1.950)
Control variables	Y	Y	Y	Y
# of ties	3,315	3,443	2,773	1,452
# of observations	25,916	26,800	19,515	20,229
R^2	0.008	0.008	0.012	-0.158
F-statistic	3.959	3.875	3.766	41.792
RMSE	0.124	0.125	0.116	0.432

Note: Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, control variables' coefficients omitted, time- and tie-fixed effects included across all models

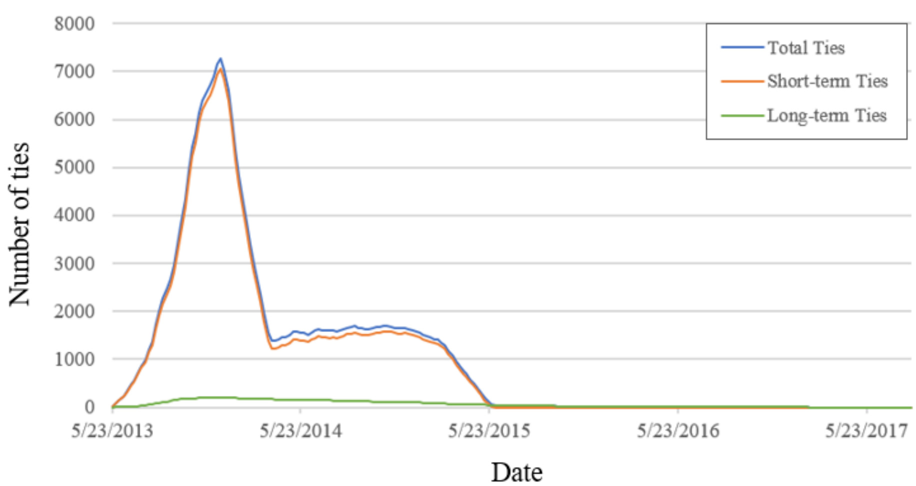

Figure 8. Heterogeneity of Tie Length

We differentiated short-term and long-term ties by setting a four-month (17-week) threshold for tie duration. As can be seen in Figure 8, the 17-week threshold clearly splits ties into two groups, where the long-term ties were stable and experienced slow increases followed by decreases over time. However, the short-term ties experienced dramatic change. Before April 2014, the short-term ties showed a pattern of rapid increase and decrease. Comparing Figure 8 with Figure 5, we can see that the building of short-term ties is aligned with the increase in users before April 2014, which may have resulted from promotional policies at the beginning of the platform. When incentive or promotional events disappear, customers may not visit the website again.[4] After April 2014, the remaining short-term ties experienced a slower decay. We

[4] Please note that our differentiation is based on the length of the tie duration rather than the user registration time. Promotional activities may bring in new users. What we care about is how long the users remain active on the website.

observed both short-term and long-term ties gradually disappearing by May 2015. Compared to Figure 5, this time period is aligned with a stable number of active users. After May 2015, even though Figure 5 still shows some active users, Figure 8 shows almost no ties remaining active, indicating the death of the website.

Interestingly, the inverted U-shaped effect of interest alignment mainly applies to long-term ties. We conducted a subsample analysis, as reported in Appendix Table A5. As we can see, the results on long-term ties are consistent with our main model (inverted U-shaped effect of interest alignment and significant interaction effect), implying the effectiveness of promotional efforts on loyal customer retention. However, on short-term ties, the estimation result only indicates a decreasing effect of interest alignment on tie strength. In other words, short-term ties are hard for sellers to maintain. Even if platforms can attract short-term ties, it is difficult for sellers to maintain them if they cannot be converted to long-term ties. The low fraction of long-term ties and the fragility of short-term ties imply that the ultimate shutdown of Douban Dongxi could be attributed to the failure to convert short-term ties to long-term ties. The long-term results also validate the generalizability of our findings. Since the results mainly target loyal customers, the platform's rising period or falling period had limited influence on our results, which is consistent with the results we obtained in Section 6.2, where we changed the study time periods. Even though the platform we studied has shut down, our findings can still apply to other active social commerce platforms.

5.6 From Tie Decay to Tie Break

We further extended our analysis from tie decay to tie break using a survival model following Jin et al. (2020). To estimate the time-varying covariates (such as promotion activities) that may contribute to tie survival, we built a time-dependent Cox proportional-hazards regression model as follows:

$$H_i(t) = H_0(t)exp\{\alpha + X_{i,t-1}\Gamma + Control_{i,t-1} + \eta_i + \theta_t + \varepsilon_{i,t}\}, \quad (6)$$

where $H_i(t)$ is the survival function depending only on time and following the Weibull distribution; $X_{i,t-1}$ is a vector of covariates ($Interest\_Alignment_{i,t-1}$, $Interest\_Alignment_{i,t-1}^2$, and $Prod\_Num\_Seller_{i,t-1}$) and their interaction terms; and Γ is the coefficients of covariates. $Control_{i,t-1}$ is a vector of the same control variables as the main model; α is the constant item; η_i is the tie-fixed effect; θ_t is the week-fixed effect; and $\varepsilon_{i,t}$ is the error term. Among the control variables, we removed the number of sellers' and customers' ties since their change is equivalent to the break of other ties in the network, which causes interdependency among data instances. For the sake of this study, we assumed that the data instances were independent of each other; we leave more complicated models addressing the issue for future research.

The estimation results are reported in Appendix Table A6, which varies the time period of samples. (To ensure no later interactions among ties, we extended the samples to cover the entire period through 2017.) As we can see, interest alignment and the interaction effect still have the same impacts as discovered in the main model, showing the alignment between tie decay and tie break in social commerce.

5.7 Tie Decay Outcome

While our analysis focused on the change in tie strength, there may be concerns about the extent to which strengthening a tie would impact social commerce. To address this concern, we derived a new measure $TieStrength_{i,t} \times Customer\_Friends_{i,t}$ as the dependent variable, where $Customer\_Friends_{i,t}$ is measured by the number of customer i's total ties in week t. This measure reflects the possibility that a promotion may go through a tie to a customer and then be propagated to the customer's friends. If a customer has many friends, this tie would be more important to maintain.

As shown in Table 7, the results of this analysis are consistent with the main model, showing that interest alignment has an inverted U-shaped relationship with the potential impact of tie decay and that the relationship is reinforced by the seller's promotion count.

6 Discussion

6.1 Theoretical Contribution

From a theoretical perspective, given the pivotal role of social ties in social commerce, this study fills a piece of the puzzle in the literature on tie decay and relationship maintenance in social commerce by investigating the rarely studied antecedents of social tie decay. It extends existing relationship maintenance studies on generic friendship to the unique context of social commerce, where ties are influenced by sellers' promotion activities. Our study highlights the unique impact of promotional activities on social tie decay and the distinct mechanisms behind relationship evolution in the generic social network context. It also extends traditional CRM literature beyond the organizational context and sheds light on individual social commerce sellers with intermediary roles where ties are the major promotion channels. In particular, we find that sellers' interest alignment with customers facilitates tie strength when the alignment level is low and weakens social ties when the alignment level is high. This effect could arise from the joint effect of the customers' need to see well-matched products to lower search costs and their need for novelty and surprise in promotions.

Table 7. Results of Tie Decay Outcome

	(1)	(2)
DV: ***$TieStrength_{i,t} \times Customer\_Friends_{i,t}$***	**OLS**	**2SLS**
Direct effects		
$Interest\_Alignment_{i,t-1}$	1.332^{***} (0.296)	2.702^{***} (0.980)
$Interest\_Alignment_{i,t-1}^2$	-7.202^{***} (0.722)	-12.398^{***} (3.255)
$Prod\_Num\_Seller_{i,t-1}$	0.009 (0.011)	0.003 (0.036)
Interaction effects		
$Interest\_Alignment_{i,t-1} \times Prod\_Num\_Seller_{i,t-1}$	-0.461^{***} (0.116)	-0.789 (0.664)
$Interest\_Alignment_{i,t-1}^2 \times Prod\_Num\_Seller_{i,t-1}$	2.325^{***} (0.290)	4.500^{**} (2.084)
Constant	0.154^{***} (0.051)	
Control variables	Y	Y
# of ties	3,562	3,292
# of observations	27,083	24,353
R^2	0.194	0.015
F-statistic	24.725	3.797

Note: Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, control variables' coefficients omitted, time- and tie-fixed effects included across all models

Meanwhile, we show a reinforcement effect of promotion count. This extends previous advertising studies on the annoying effect of ads (Goldstein et al., 2014; Todri et al., 2020), which argue that too many promotions could cause adverse effects. Our framework delivers the new insights that repeated advertisements can lead to a reduced interest alignment, which leads to a negative effect, while promotion count may not generate a negative effect directly.

These findings carry unique significance in today's rapidly evolving social commerce landscape, particularly in light of the prevalent trend of recommender systems offering customers an array of homogeneous content. It should be noted that the literature contains a discussion on the writing style of firm-customer interactions, such as sentiment, readability, comprehensiveness, and grammatical errors (Singh et al., 2014). These studies are relevant to our research, although our study focuses on the promotion content rather than style. Prior studies have found that users may change their preferences based on different communication styles (Singh et al., 2014). Our finding also indicates this possibility; however, we focus on the difference between promotion and customer interest instead of a change in customer interest.

6.2 Practical Implications

Our findings could enlighten social commerce sellers by providing additional perspectives on how to maintain ties with customers, which are often fragile yet crucial to social commerce success. Potential customers of a social commerce seller may have heterogeneous interests and preferences. Our results indicate that the optimal strategy for sellers is to find a moderate interest alignment with customers to achieve a balance between product fit and novelty. An occasional divergence from currently posted products or content would also benefit sellers by attracting customers' attention and strengthening their connections.

Additionally, our study suggests that platforms could introduce design features that provide more guidance to sellers based on back-end interaction data and customer profiles, facilitating the maintenance of enduring and stable customer-seller ties through promotional activities. Firms that want to leverage social commerce sellers as sales channels can also optimize their seller selection, given the optimal efforts of individual sellers, which will affect reachable customers.

7 Conclusion

In this study, we investigated the impact of sellers' promotional activities on tie decay in social commerce. Using a dataset from one large social commerce website in China, we found that the alignment between seller promotions and user interest has an inverted U-shaped relationship with tie strength. We also observed that promotion count reinforces this effect, where more promotions push the inverted U-shaped curve flatter to the right. These effects were most pronounced on customers with higher loyalty. This study contributes to both academia and industry.

This study could be extended in several directions by future research. First, we leveraged users' commenting activities to measure ties and tie strength. Yet social ties can be measured in many other ways, such as likes, bookmarks, shares, and follows. Limited by the data availability in our research setting, we did not use these other measurements, so future studies could test the findings using other measures. Second, our analyses were all based on data collected in China. It would be beneficial to extend the study to other cultures and websites to test the generalizability of our findings. Lastly, many other factors may exist that affect tie decay in social commerce, which would be worth exploring in the future. For instance, directly pushing customized content to target customers is a unique strategy for some social commerce channels, such as WeChat. The existence of customized channels could complicate the problem and may be a very valuable moderator to explore. Beyond these, non-commerce activities are very interesting factors that have not been investigated in our context, and the tangle of commercial and non-commercial activities would be a very interesting topic for future research.

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Appendix: Control Variables Calculation

To measure common friends, we followed Song et al. (2019) in counting four types of common friends in the social network. Figure A1 summarizes the definitions.

- *Common_Friends_A*$_{i,t-1}$ is the number of users who are commented on by the seller and the customer in tie *i*. They serve as sellers in the tie with the users in tie *i*.
- *Common_Friends_B*$_{i,t-1}$ is the number of users who comment on the seller and are commented on by the customer in tie *i*. The users in tie *i* maintain the same role when they form another tie with these common friends.
- *Common_Friends_C*$_{i,t-1}$ is the number of users who are commented on by the seller and comment on the customer in tie *i*. The users in tie *i* play the inverse role when they form another tie with these common friends.
- *Common_Friends_D*$_{i,t-1}$ is the number of users who comment on the seller and the customer in tie *i*. They are customers in the tie with the users in tie *i*.

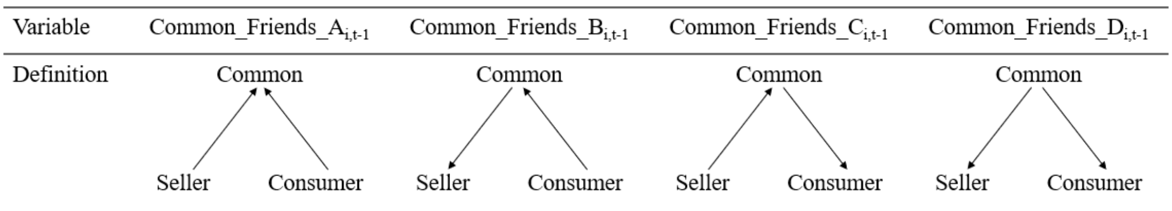

Figure A1. Definitions of Common Friends

We computed the measures of user diversity as follows. Figure A2 illustrates the relationship between these interest measures.

- *Diversity_Customer*$_{i,t-1}$ is the cosine similarity calculated based on the textual contents of products (1) posted by the seller and commented on by the customer in tie *i* (Part C in Figure A2) and (2) posted by other sellers outside the tie *i* and commented on by the customer in tie *i* (Part B in Figure A2), including products' titles and descriptions (in week *t*-1). It measures the interest diversity of the customer.
- *Diversity_Seller*$_{i,t-1}$ is the cosine similarity calculated based on the textual contents of products (1) posted by the seller and commented on by the customer in tie *i* (Part C in Figure A2) and (2) posted by the seller but not commented on by the customer in tie *i* (Part A in Figure A2), including products' titles and descriptions (in week *t*-1). It measures the posting diversity of the seller.

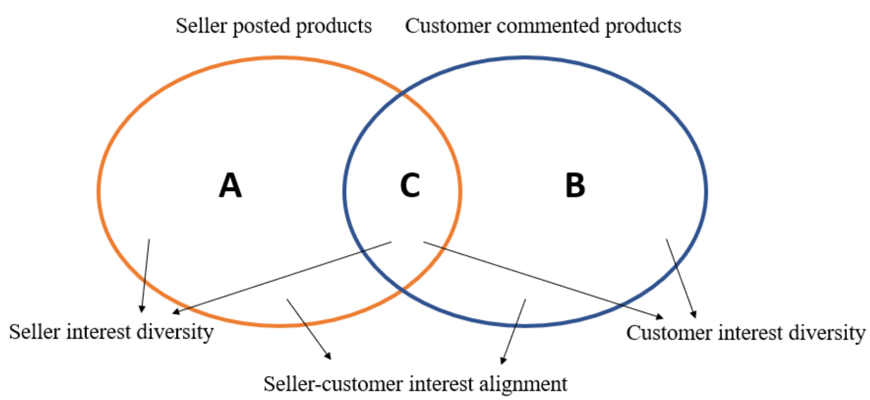

Figure A2. Seller-Customer Interest Alignment and Diversity

For the sentiment-related measures, we assessed the sentiment level of the product description contents using the lexicon of sentiment word ontology published by Xu et al. (2008). We conducted word segmentation and assigned sentiment value to each word (zero for neutral words not in the lexicon). We averaged all sentiment values of words (i.e., the sum of sentiment values divided by the number of words in the sentences) to get the sentiment of a piece of text. If there was no textual description, the sentiment was regarded as zero (i.e., neutral).

Table A1. Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(1) $TieStrength_{i,t}$	1.00																			
(2) $Prod\_Num\_Seller_{i,t}$	0.06	1.00																		
(3) $Interest\_Alignment_{i,t}$	0.13	0.11	1.00																	
(4) $Common\_Friends\_A_{i,t}$	0.11	0.23	0.28	1.00																
(5) $Common\_Friends\_B_{i,t}$	0.07	0.17	0.26	0.77	1.00															
(6) $Common\_Friends\_C_{i,t}$	0.16	0.19	0.26	0.73	0.62	1.00														
(7) $Common\_Friends\_D_{i,t}$	0.09	0.11	0.20	0.49	0.62	0.73	1.00													
(8) $Diversity\_Seller_{i,t}$	0.01	0.09	0.25	0.05	0.02	0.04	0.02	1.00												
(9) $Diversity\_Customer_{i,t}$	0.00	0.06	0.22	0.07	0.07	0.05	0.05	0.95	1.00											
(10) $Reply\_Sent_{i,t}$	0.02	0.02	0.01	0.03	0.04	0.02	0.02	-0.02	-0.02	1.00										
(11) $Prod\_Sent\_Seller_{i,t}$	0.01	0.04	-0.01	-0.02	-0.00	-0.02	-0.00	-0.07	-0.05	0.00	1.00									
(12) $Reply\_Num\_Seller_{i,t}$	0.00	0.28	-0.01	0.14	0.17	0.10	0.11	0.29	0.38	0.02	-0.01	1.00								
(13) $Reply\_Sent\_Seller_{i,t}$	-0.00	0.06	-0.01	0.03	0.04	0.02	0.03	-0.01	-0.00	0.02	0.02	-0.01	1.00							
(14) $Tie\_Num\_Seller_{i,t}$	-0.03	0.12	-0.01	0.11	0.17	0.06	0.11	0.55	0.63	-0.01	-0.02	0.67	0.02	1.00						
(15) $Prod\_Num\_Customer_{i,t}$	0.04	0.04	0.12	0.27	0.32	0.23	0.20	-0.12	-0.11	0.05	0.02	0.01	0.03	-0.06	1.00					
(16) $Prod\_Sent\_Customer_{i,t}$	0.02	0.05	0.11	0.14	0.15	0.11	0.11	-0.08	-0.06	0.04	0.02	0.04	0.02	-0.02	0.24	1.00				
(17) $Com\_Num\_Customer_{i,t}$	0.25	0.02	0.16	0.19	0.20	0.28	0.29	-0.07	-0.08	0.02	0.01	-0.03	-0.01	-0.07	0.20	0.09	1.00			
(18) $Com\_Sent\_Customer_{i,t}$	0.04	0.01	0.09	0.09	0.10	0.11	0.10	-0.02	-0.02	0.01	-0.00	-0.02	0.01	-0.03	0.13	0.08	0.11	1.00		
(19) $Tie\_Num\_Customer_{i,t}$	0.05	0.00	0.22	0.35	0.35	0.31	0.28	-0.16	-0.16	0.03	0.01	-0.08	0.01	-0.13	0.28	0.14	0.42	0.16	1.00	
(20) $Tie\_Age_{i,t}$	0.02	-0.06	0.31	-0.02	-0.03	-0.00	-0.01	0.40	0.35	-0.03	-0.01	-0.14	-0.06	-0.04	-0.09	-0.06	-0.02	0.01	-0.03	1.00

Table A2. Complete Regression Results of the Main Model

	Model 1	Model 2	Model 3	Model 4
DV: $TieStrength_{i,t}$	OLS	OLS	2SLS	2SLS
Direct effects				
$Interest\_Alignment_{i,t-1}$	0.138** (0.067)	0.326*** (0.087)	0.385** (0.173)	0.659* (0.374)
$Interest\_Alignment_{i,t-1}^2$	-1.139*** (0.157)	-2.098*** (0.213)	-1.797*** (0.488)	-3.531*** (1.132)
$Prod\_Num\_Seller_{i,t-1}$	0.006*** (0.001)	0.003 (0.003)	0.013** (0.005)	0.001 (0.012)
Interaction effects				
$Interest\_Alignment_{i,t-1} \times Prod\_Num\_Seller_{i,t-1}$		-0.117*** (0.034)		-0.223 (0.213)
$Interest\_Alignment_{i,t-1}^2 \times Prod\_Num\_Seller_{i,t-1}$		0.570*** (0.085)		1.168* (0.623)
Control variables				
$TieStrength_{i,t-1}$	0.013** (0.006)	0.010 (0.006)	0.012 (0.023)	0.003 (0.021)
$Common\_Friends\_A_{i,t-1}$	0.006 (0.004)	0.003 (0.004)	0.001 (0.006)	-0.004 (0.006)
$Common\_Friends\_B_{i,t-1}$	0.003 (0.005)	0.003 (0.005)	0.009 (0.007)	0.007 (0.007)
$Common\_Friends\_C_{i,t-1}$	0.016*** (0.006)	0.015*** (0.006)	0.019** (0.009)	0.017* (0.009)
$Common\_Friends\_D_{i,t-1}$	0.005 (0.005)	0.003 (0.005)	0.005 (0.008)	0.001 (0.008)
$Diversity\_Seller_{i,t-1}$	-0.042 (0.046)	-0.039 (0.046)	-0.103 (0.068)	-0.087 (0.070)
$Diversity\_Customer_{i,t-1}$	-0.031 (0.030)	-0.033 (0.030)	0.008 (0.044)	-0.007 (0.044)
$Reply\_Sent_{i,t-1}$	0.004 (0.007)	0.004 (0.007)	0.008 (0.011)	0.009 (0.011)
$Prod\_Sent\_Seller_{i,t-1}$	-0.006 (0.004)	-0.006 (0.004)	-0.009** (0.004)	-0.008** (0.004)
$Reply\_Num\_Seller_{i,t-1}$	0.002 (0.001)	0.002* (0.001)	0.000 (0.002)	0.001 (0.002)
$Reply\_Sent\_Seller_{i,t-1}$	-0.000 (0.004)	-0.000 (0.004)	-0.000 (0.004)	-0.001 (0.004)
$Tie\_Num\_Seller_{i,t-1}$	-0.008** (0.004)	-0.007* (0.004)	-0.005 (0.005)	-0.003 (0.006)
$Prod\_Num\_Customer_{i,t-1}$	-0.001 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.003 (0.002)
$Prod\_Sent\_Customer_{i,t-1}$	0.004 (0.005)	0.005 (0.005)	0.009 (0.006)	0.010 (0.006)
$Com\_Num\_Customer_{i,t-1}$	0.011*** (0.001)	0.010*** (0.001)	0.011*** (0.002)	0.010*** (0.002)
$Com\_Sent\_Customer_{i,t-1}$	-0.004 (0.003)	-0.003 (0.003)	-0.004 (0.007)	-0.003 (0.007)
$Tie\_Num\_Customer_{i,t-1}$	-0.011*** (0.003)	-0.010*** (0.003)	-0.012** (0.005)	-0.012** (0.005)
$Tie\_Age_{i,t-1}$	0.002 (0.002)	0.002 (0.002)	0.004 (0.004)	0.004 (0.004)
Constant	0.061*** (0.014)	0.065*** (0.015)		
Time-fixed effect	Y	Y	Y	Y
Tie-fixed effect	Y	Y	Y	Y
# of ties	3,562	3,562	3,292	3,292
# of observations	27,083	27,083	24,353	24,353
R^2	0.158	0.162	0.011	0.009
F-statistic	13.967	18.031	3.762	3.830
RMSE	0.130	0.130	0.122	0.122
Instruments			Y	Y
Underidentification test			1,675.113***	630.028***
Weak identification test			415.746	212.374
Overidentification test			7.564*	8.307

Note: Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A3. First-stage Regression Results of 2SLS

	DV: *Interest_Alignment*$_{i,t-1}$		DV: *Interest_Alignment*$_{i,t-1}^2$		DV: *Prod_Num_Seller*$_{i,t-1}$		DV: *Interest_Alignment*$_{i,t-1}$ ×*Prod_Num_Seller*$_{i,t-1}$	DV: *Interest_Alignment*$_{i,t-1}^2$ ×*Prod_Num_Seller*$_{i,t-1}$
	Model 3	**Model 4**	**Model 3**	**Model 4**	**Model 3**	**Model 4**	**Model 4**	**Model 4**
Interest_Alignment$_{i,t-2}$	0.463*** (0.020)	0.411*** (0.023)	-0.029** (0.011)	-0.023 (0.014)	-0.136 (0.279)	-0.243 (0.310)	0.631*** (0.075)	0.050 (0.028)
Interest_Alignment$_{i,t-2}^2$	0.381*** (0.050)	0.420*** (0.062)	0.777*** (0.038)	0.751*** (0.048)	-0.986 (0.681)	-0.953 (0.777)	-0.351 (0.225)	0.563*** (0.097)
Prod_Num_Seller$_{i,t-2}$	0.000*** (0.000)	-0.002*** (0.000)	0.000*** (0.000)	0.000 (0.000)	0.174*** (0.005)	0.151*** (0.011)	-0.014*** (0.002)	-0.002** (0.001)
Interest_Alignment$_{i,t-2}$× *Prod_Num_Seller*$_{i,t-2}$		0.020*** (0.005)		-0.005 (0.004)		0.190 (0.118)	0.283*** (0.030)	-0.006 (0.014)
Interest_Alignment$_{i,t-2}^2$× *Prod_Num_Seller*$_{i,t-2}$		-0.034* (0.014)		0.019 (0.011)		-0.250 (0.298)	-0.032 (0.094)	0.292*** (0.045)
Interest_Alignment_Others$_{i,t-1}$	-0.033* (0.013)	-0.018 (0.015)	-0.017** (0.006)	-0.016* (0.006)	8.277*** (0.622)	9.052*** (0.658)	1.884*** (0.148)	0.507*** (0.049)
Interest_Alignment_Others$_{i,t-1}^2$	0.170*** (0.050)	0.104 (0.063)	0.098*** (0.024)	0.095** (0.030)	-21.231*** (2.680)	-32.209*** (3.114)	-6.247*** (0.683)	-1.554*** (0.221)
Prod_Num_Others$_{i,t-1}$	-0.001 (0.001)	0.001 (0.002)	-0.000 (0.000)	0.000 (0.001)	-0.691*** (0.028)	-0.891*** (0.064)	-0.138*** (0.012)	-0.031*** (0.003)
Interest_Alignment_Others$_{i,t-1}$ × *Prod_Num_Others*$_{i,t-1}$		-0.045 (0.028)		-0.008 (0.011)		1.529 (0.920)	-0.153 (0.174)	-0.100* (0.050)
Interest_Alignment_Others$_{i,t-1}^2$ × *Prod_Num_Others*$_{i,t-1}$		0.164 (0.100)		0.022 (0.040)		6.759* (2.986)	2.224*** (0.558)	0.656*** (0.162)
TieStrength$_{i,t-1}$	0.008*** (0.001)	0.008*** (0.001)	0.004*** (0.001)	0.004*** (0.001)	0.052 (0.032)	0.049 (0.032)	0.038*** (0.010)	0.017*** (0.004)
Common_Friends_A$_{i,t-1}$	-0.000 (0.001)	-0.000 (0.001)	-0.001** (0.000)	-0.001** (0.000)	0.102*** (0.021)	0.100*** (0.021)	0.029*** (0.006)	0.008*** (0.002)
Common_Friends_B$_{i,t-1}$	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.000)	-0.000 (0.000)	0.002 (0.024)	0.003 (0.024)	0.001 (0.006)	0.001 (0.002)
Common_Friends_C$_{i,t-1}$	-0.002* (0.001)	-0.002* (0.001)	-0.001* (0.000)	-0.001* (0.000)	-0.022 (0.027)	-0.023 (0.027)	-0.002 (0.007)	0.001 (0.002)
Common_Friends_D$_{i,t-1}$	0.001 (0.001)	0.001 (0.001)	-0.000 (0.000)	-0.000 (0.000)	0.038 (0.024)	0.037 (0.024)	0.013* (0.006)	0.004* (0.002)
Diversity_Seller$_{i,t-1}$	0.009 (0.008)	0.006 (0.008)	-0.000 (0.003)	-0.000 (0.003)	4.754*** (0.277)	4.672*** (0.276)	0.894*** (0.064)	0.202*** (0.019)
Diversity_Customer$_{i,t-1}$	-0.025*** (0.005)	-0.023*** (0.005)	-0.006** (0.002)	-0.006** (0.002)	-4.389*** (0.187)	-4.339*** (0.187)	-0.851*** (0.042)	-0.196*** (0.012)
Reply_Sent$_{i,t-1}$	0.003 (0.001)	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)	-0.051 (0.040)	-0.058 (0.040)	-0.012 (0.012)	-0.004 (0.004)
Prod_Sent_Seller$_{i,t-1}$	0.002*** (0.001)	0.002*** (0.001)	0.000** (0.000)	0.000** (0.000)	0.265*** (0.019)	0.266*** (0.018)	0.048*** (0.004)	0.012*** (0.001)

Reply_Num_Seller$_{i,t-1}$	0.001*** (0.000)	0.001*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.185*** (0.006)	0.186*** (0.006)	0.033*** (0.001)	0.008*** (0.000)
Reply_Sent_Seller$_{i,t-1}$	0.000 (0.000)	-0.000 (0.001)	0.000 (0.000)	0.000 (0.000)	0.072*** (0.018)	0.069*** (0.018)	0.015*** (0.004)	0.005*** (0.001)
Tie_Num_Seller$_{i,t-1}$	0.002** (0.001)	0.002** (0.001)	0.001*** (0.000)	0.001*** (0.000)	-0.097*** (0.019)	-0.089*** (0.019)	-0.015** (0.005)	-0.004** (0.001)
Prod_Num_Customer$_{i,t-1}$	0.002*** (0.000)	0.002*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	-0.011 (0.007)	-0.013 (0.007)	0.004* (0.002)	0.002* (0.001)
Prod_Sent_Customer$_{i,t-1}$	0.002 (0.001)	0.002* (0.001)	0.000 (0.000)	0.000 (0.000)	0.022 (0.026)	0.023 (0.026)	0.007 (0.006)	0.001 (0.002)
Com_Num_Customer$_{i,t-1}$	0.002*** (0.000)	0.002*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.003 (0.006)	0.004 (0.006)	0.005** (0.002)	0.002*** (0.001)
Com_Sent_Customer$_{i,t-1}$	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.017 (0.015)	0.017 (0.015)	-0.001 (0.004)	-0.002 (0.001)
Tie_Num_Customer$_{i,t-1}$	0.002*** (0.000)	0.002*** (0.000)	0.000*** (0.000)	0.001*** (0.000)	-0.018 (0.015)	-0.018 (0.015)	-0.000 (0.004)	0.000 (0.001)
Tie_Age$_{i,t-1}$	0.002*** (0.000)	0.002*** (0.000)	0.000 (0.000)	0.000 (0.000)	-0.021 (0.014)	-0.025 (0.014)	0.004 (0.003)	0.000 (0.001)
Time-fixed effect	Y	Y	Y	Y	Y	Y	Y	Y
Tie-fixed effect	Y	Y	Y	Y	Y	Y	Y	Y
# of ties	3,292	3,292	3,292	3,292	3,292	3,292	3,292	3,292
# of observations	24,353	24,353	24,353	24,353	24,353	24,353	24,353	24,353
F-statistic	466.97	179.67	372.96	119.28	466.34	122.62	135.67	95.71

Note: Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4. Summary Statistics

Variable	Obs.	Mean	*SD*	Min	Max
$TieStrength_{i,t}$	23,891	1.506	9.284	0	266
$Interest\_Alignment_{i,t}$	23,891	0.290	0.335	0	1
$Prod\_Num\_Seller_{i,t}$	23,891	106.943	82.68	1	554
$Common\_Friends\_A_{i,t}$	23,891	1.101	0.497	0	5
$Common\_Friends\_B_{i,t}$	23,891	1.101	0.500	0	4
$Common\_Friends\_C_{i,t}$	23,891	0.058	0.292	0	4
$Common\_Friends\_D_{i,t}$	23,891	1.512	12.823	0	244
$Diversity\_Seller_{i,t}$	23,891	0.216	0.320	0	0.987
$Diversity\_Customer_{i,t}$	23,891	0.012	0.063	0	0.770
$Reply\_Sent_{i,t}$	23,891	0.064	0.349	-4	9
$Prod\_Sent\_Seller_{i,t}$	23,891	0.119	0.058	-0.030	0.515
$Reply\_Num\_Seller_{i,t}$	23,891	0.512	1.319	0	46
$Tie\_Num\_Seller_{i,t}$	23,891	90.855	76.252	1	227
$Prod\_Num\_Customer_{i,t}$	23,891	4.140	24.192	0	390
$Prod\_Sent\_Customer_{i,t}$	23,891	0.008	0.036	-0.004	0.514
$Com\_Num\_Customer_{i,t}$	23,891	6.250	38.096	0	600
$Com\_Sent\_Customer_{i,t}$	23,891	0.058	0.248	-3.500	7
$Tie\_Num\_Customer_{i,t}$	23,891	1.627	1.429	1	14
$Tie\_Age_{i,t}$	23,891	9.170	6.735	0	28
$Avg\_Price_{i,t}$	23,891	225.333	501.006	1	16,409.430

Table A5. Full Regression Results for Short-term and Long-term Ties

Tie type	Short-term ties	Long-term ties
DV: $TieStrength_{i,t}$	(1)	(2)
	OLS	OLS
Direct effects		
$Interest\_Alignment_{i,t-1}$	0.026 (0.036)	0.778^{**} (0.366)
$Interest\_Alignment_{i,t-1}^2$	-0.613^{***} (0.098)	-3.639^{***} (0.740)
$Prod\_Num\_Seller_{i,t-1}$	-0.001 (0.001)	0.022 (0.018)
Interaction effects		
$Interest\_Alignment_{i,t-1} \times$ $Prod\_Num\_Seller_{i,t-1}$	0.018 (0.014)	-0.348^{**} (0.149)
$Interest\_Alignment_{i,t-1}^2 \times$ $Prod\_Num\_Seller_{i,t-1}$	-0.014 (0.041)	1.178^{***} (0.304)
Control variables		
$TieStrength_{i,t-1}$	-0.009^{*} (0.005)	-0.000 (0.013)
$Common\_Friends\_A_{i,t-1}$	0.002 (0.002)	-0.003 (0.011)
$Common\_Friends\_B_{i,t-1}$	-0.002 (0.002)	0.003 (0.014)
$Common\_Friends\_C_{i,t-1}$	-0.006^{**} (0.003)	0.020 (0.014)
$Common\_Friends\_D_{i,t-1}$	0.001 (0.002)	-0.003 (0.014)
$Diversity\_Seller_{i,t-1}$	-0.001 (0.019)	-0.026 (0.165)
$Diversity\_Customer_{i,t-1}$	-0.011 (0.012)	-0.112 (0.127)

$Reply\_Sent_{i,t-1}$	-0.005 (0.003)	0.032 (0.032)
$Prod\_Sent\_Seller_{i,t-1}$	-0.001 (0.002)	-0.023 (0.017)
$Reply\_Num\_Seller_{i,t-1}$	0.001** (0.001)	0.003 (0.005)
$Reply\_Sent\_Seller_{i,t-1}$	-0.002 (0.002)	0.010 (0.017)
$Tie\_Num\_Seller_{i,t-1}$	0.001 (0.002)	-0.011 (0.011)
$Prod\_Num\_Customer_{i,t-1}$	0.002*** (0.001)	-0.008* (0.005)
$Prod\_Sent\_Customer_{i,t-1}$	-0.004** (0.002)	0.025 (0.020)
$Com\_Num\_Customer_{i,t-1}$	0.001 (0.001)	0.019*** (0.004)
$Com\_Sent\_Customer_{i,t-1}$	0.001 (0.002)	-0.008 (0.010)
$Tie\_Num\_Customer_{i,t-1}$	-0.004** (0.002)	-0.011 (0.008)
$Tie\_Age_{i,t-1}$	-0.008*** (0.001)	0.020** (0.008)
Constant	0.030*** (0.007)	0.104* (0.061)
Time-fixed effect	Y	Y
Tie-fixed effect	Y	Y
# of ties	3,260	302
# of observations	20,416	6,667
R^2	0.155	0.155
F-statistic	13.132	6.655
RMSE	0.044	0.238
Note: Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.		

Table A6. Survival Model Results

Sample period	**Before February 26, 2015**	**Full sample**
DV: End_Time	**(1)**	**(2)**
Direct effects		
$Interest\_Alignment_{i,t-1}$	-3.834*** (0.166)	-2.851*** (0.115)
$Interest\_Alignment_{i,t-1}^2$	10.358*** (0.458)	8.006*** (0.287)
$Prod\_Num\_Seller_{i,t-1}$	0.013 (0.009)	0.015** (0.007)
Interaction effects		
$Interest\_Alignment_{i,t-1} \times$ *$Prod\_Num\_Seller_{i,t-1}$*	0.633*** (0.104)	0.449*** (0.077)
$Interest\_Alignment_{i,t-1}^2 \times$ *$Prod\_Num\_Seller_{i,t-1}$*	-1.457*** (0.279)	-0.803*** (0.192)
Control variables		
$Common\_Friends\_A_{i,t-1}$	0.907*** (0.035)	0.952*** (0.036)
$Common\_Friends\_B_{i,t-1}$	0.650*** (0.039)	0.688*** (0.040)
$Common\_Friends\_C_{i,t-1}$	0.445*** (0.051)	0.315*** (0.051)
$Common\_Friends\_D_{i,t-1}$	0.924*** (0.044)	1.101*** (0.044)
$Diversity\_Seller_{i,t-1}$	1.173*** (0.042)	1.266*** (0.029)
$Diversity\_Customer_{i,t-1}$	-1.272*** (0.030)	-1.516*** (0.024)

Reply_Sent$_{i,t-1}$	0.384*** (0.073)	0.417*** (0.073)
Prod_Sent_Seller$_{i,t-1}$	0.084*** (0.012)	0.031*** (0.007)
Reply_Num_Seller$_{i,t-1}$	0.049*** (0.003)	0.036*** (0.002)
Reply_Sent_Seller$_{i,t-1}$	-0.077*** (0.012)	-0.043*** (0.009)
Prod_Num_Customer$_{i,t-1}$	-0.041*** (0.006)	-0.063*** (0.006)
Prod_Sent_Customer$_{i,t-1}$	0.087*** (0.028)	0.144*** (0.025)
Com_Num_Customer$_{i,t-1}$	0.166*** (0.006)	0.163*** (0.005)
Com_Sent_Customer$_{i,t-1}$	-0.004 (0.016)	-0.005 (0.015)
Constant	4.128*** (0.013)	4.197*** (0.010)
# of observations	77,691	137,587
# of ties	5,636	5,891
# of failures	4,079	4,574
Log likelihood	-231,656.500	-501,884.000
Chi-square	21,447.430***	29,618.000***
Akaike crit. (AIC)	463,355.0	1,003,810.0
Bayesian crit. (BIC)	463,549.5	1,004,016.0

Note: Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

About the Authors

Bingqing Song is a PhD student in the Department of Information Systems at City University of Hong Kong. She received her bachelor's degree from the School of Management at Huazhong University of Science and Technology. Her research interests focus on artificial intelligence, machine learning, social networks, and e-commerce. She has published her work in *Information Technology and People.*

Yidi Liu is an assistant professor of information systems at the School of Management and Economics, the Chinese University of Hong Kong, Shenzhen (CUHK-Shenzhen). He received his PhD in information systems from the City University of Hong Kong, and a bachelor's degree in logistics management from Huazhong University of Science and Technology. His research interest covers digital economy, artificial intelligence, fintech, and network analysis. His research has appeared in *Information Systems Research, Information Technology and People, Decision Support Systems*, among other outlets.

Xin Li is a professor in the Department of Management and Marketing at the Hong Kong Polytechnic University. He received his PhD in management information systems from the University of Arizona. He received his bachelor's and master's degrees from the Department of Automation at Tsinghua University, China. His research interests include digital economy, machine learning, social networks, and applied econometrics. His work has appeared in *MIS Quarterly, Information Systems Research, Journal of Management Information Systems, INFORMS Journal on Computing,* and *Decision Support Systems*, among other outlets.